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SMART AMBULANCE DETECTION AND PRIORITIZATION IN TRAFFIC USING DEEP-LEARNING

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Abstract : Traffic congestion in urban areas presents significant challenges, particularly for emergency vehicles such as ambulances, which require swift and unobstructed passage to save lives. This paper proposes an intelligent traffic control system based on ambulance detection to resolve this issue. Using YOLOv8 deep learning algorithm, the system can identify ambulances in real-time using surveillance cameras positioned at intersections and along major routes. Upon detection, the system dynamically adjusts traffic signals to create a clear path for the ambulance. By interfacing the detection results with the microcontroller ESP8266, the traffic signals are adjusted. The implementation of an intelligent traffic control system based on ambulance detection presents a promising solution to the critical issue of emergency vehicle delays in urban environments.

***IndexTerms* - You Only Look Once (YOLO) .**

I. INTRODUCTION

The rapid increase in urbanization and the subsequent rise in the number of vehicles on the roads have led to significant traffic congestion issues worldwide. Among the most critical challenges faced in densely populated urban areas is the timely passage of emergency vehicles, particularly ambulances. Delays in reaching medical facilities due to traffic jams can result in life-threatening situations, underscoring the need for efficient traffic management systems. This project, titled "SMART AMBULANCE DETECTION AND PRIORITIZATION IN TRAFFIC USING DEEP LEARNING", aims to address this pressing issue by leveraging advanced deep learning techniques to develop a smart traffic control system. The primary objective of this project is to ensure that ambulances can navigate through heavy traffic swiftly and without unnecessary delays, thereby potentially saving countless lives.

The proposed system utilizes state-of-the-art deep learning algorithms to detect ambulances in real-time within traffic streams. By analyzing video feeds from traffic cameras, the system can identify the presence of an ambulance and automatically change the traffic signal to green for the lane in which the ambulance is detected, allowing it to move through intersections and congested areas without delay. This approach enhances the efficiency of emergency response services and optimizes the overall traffic flow.

This report provides a comprehensive overview of the project's scope, methodology, and implementation. It begins with a review of the current challenges in traffic management and the limitations of existing systems. The report then delves into the technical aspects of the project, including the selection of deep learning models, data collection and preprocessing, model training and evaluation, and system integration. Finally, it discusses the results obtained from the implementation.

By harnessing the power of deep learning, this project aspires to contribute to smarter, more responsive urban traffic management solutions, enhancing the safety and efficiency of emergency services on the roads.

II. TECHNICAL BLOCK DIAGRAM

2.1 Ambulance Detection and Prioritization in Traffic:

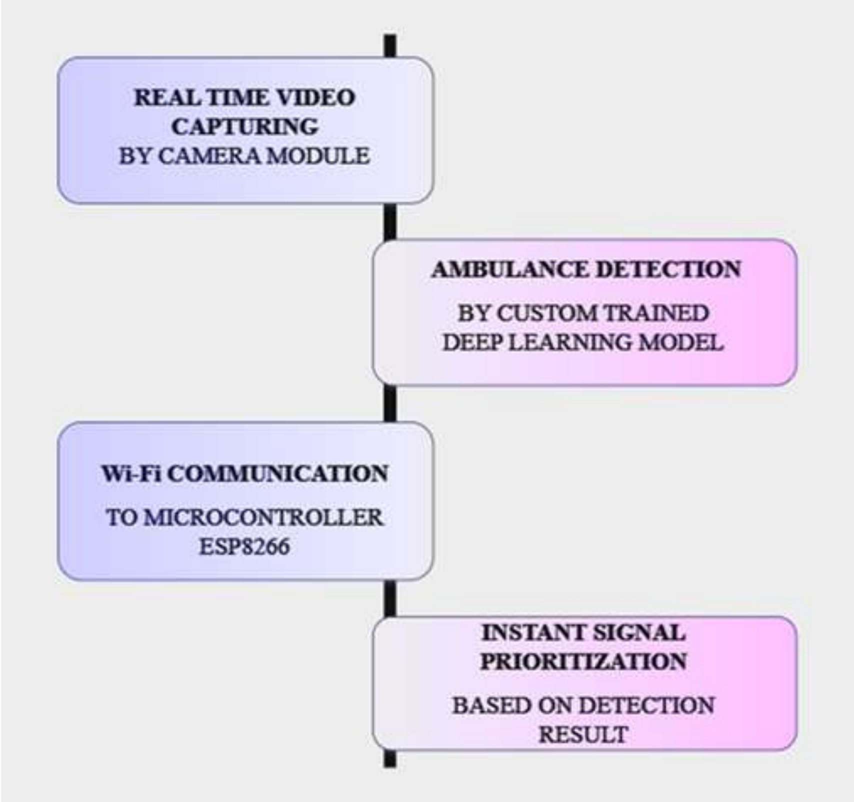

Fig 1. Ambulance Detection and Prioritization in Traffic

2.2 Development of a Custom Trained Deep Learning Model:

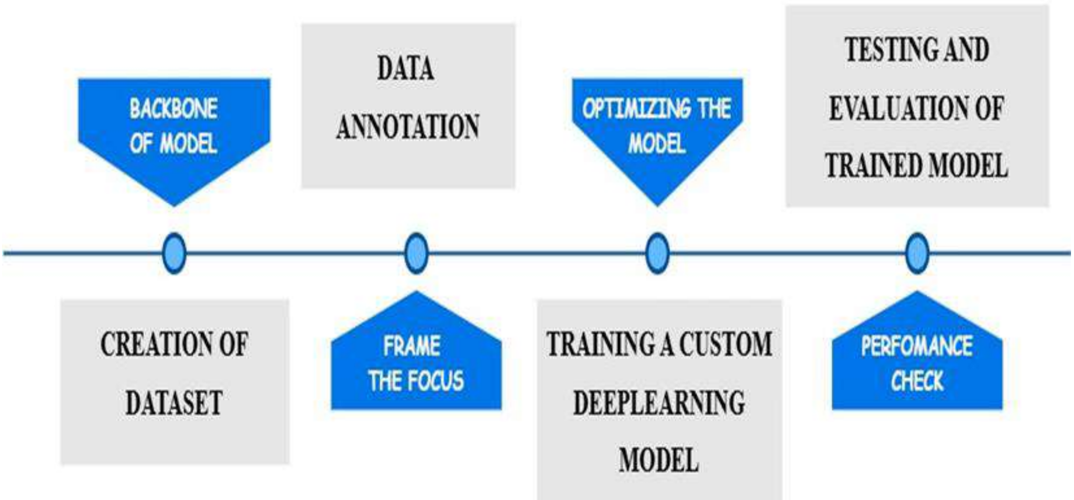

Fig 2. Development of Deep Learning Model

2.3 YOLO Algorithm:

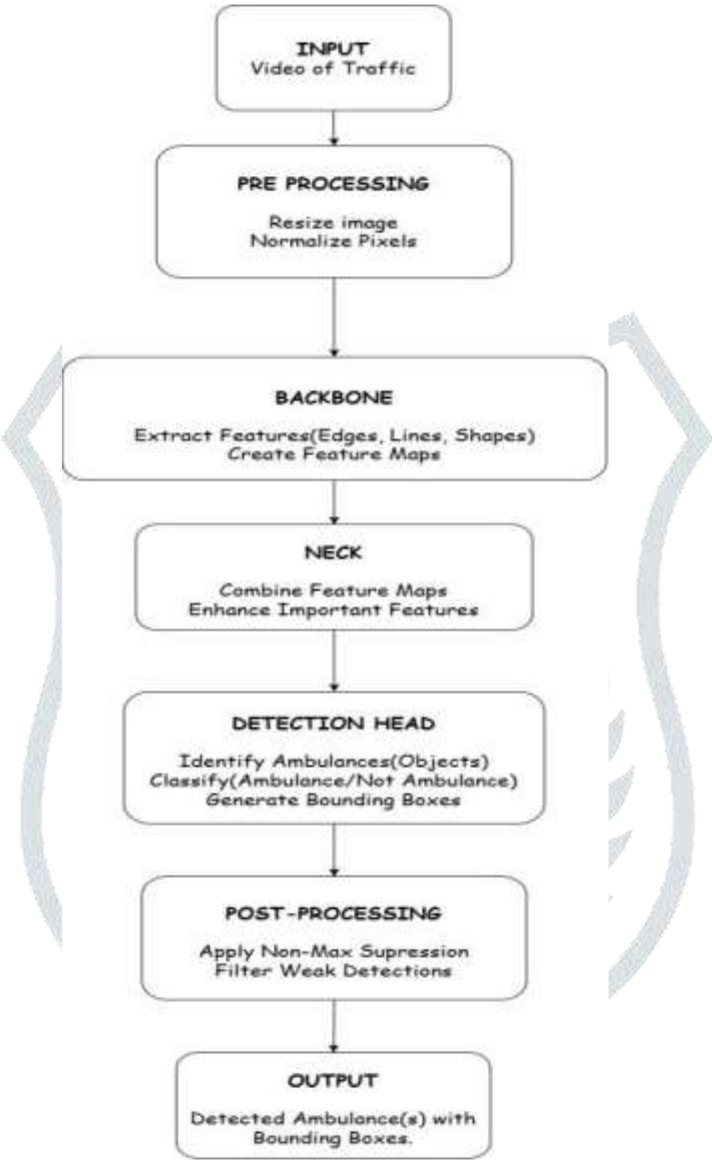

Fig 3. Yolo Algorithm

III. METHODOLOGY

The development of the traffic control system based on ambulance detection using deep learning involves several critical stages, each meticulously designed to ensure the accuracy and efficiency of the system. The methodology can be broken down into the following key steps:

3.1 Data Collection

The initial phase of the project involves data collection, a crucial step to ensure the model is trained on a diverse and representative dataset. This is achieved through web scraping techniques implemented on the Google Colab platform. Using various image source websites, we gather many images containing different types of ambulances in various traffic conditions. The images are collected from multiple sources to capture a wide range of scenarios, ensuring the robustness of the model.

3.2 Data Annotation

Once the images are collected, the next step is to annotate them, marking the exact locations of ambulances within the images. This is done using the Roboflow website, a powerful tool for labelling and annotating image data. Each image is carefully reviewed, and bounding boxes are drawn around the ambulances. These annotations are essential for training the deep learning model, as they provide the ground truth that the model learns to replicate.

Fig 4. Data Annotation

3.3 Data Splitting and Augmentation

After the annotation process, the annotated dataset is split into three parts: **training, validation**, and **testing sets**. The training set is used to teach the model, the validation set helps tune the model's parameters and prevent overfitting, and the testing set evaluates the model's performance on unseen data. This split ensures that the model can generalize well to new images and scenarios it has not encountered during training. After this, using various augmentation steps like blur, crop, brightness, noise, the dataset is increased and thus it helps to get a wide range of scenarios. This is also done using the Roboflow website.

3.4 Model Training and Evaluation

With the dataset prepared, the YOLOv8 (You Only Look Once version 8) model is selected for training. YOLO is known for its speed and accuracy in object detection tasks. The training process is initiated using a **YAML** file that contains the dataset description, including the paths to the training, validation, and testing sets. The training and evaluation of the model are conducted in Visual Studio Code, leveraging its **integrated development environment (IDE)** features to streamline the process. Various metrics such as **precision, recall,** and **the mean average precision (mAP)** are used to assess the model's performance, ensuring its reliability in real-world conditions.

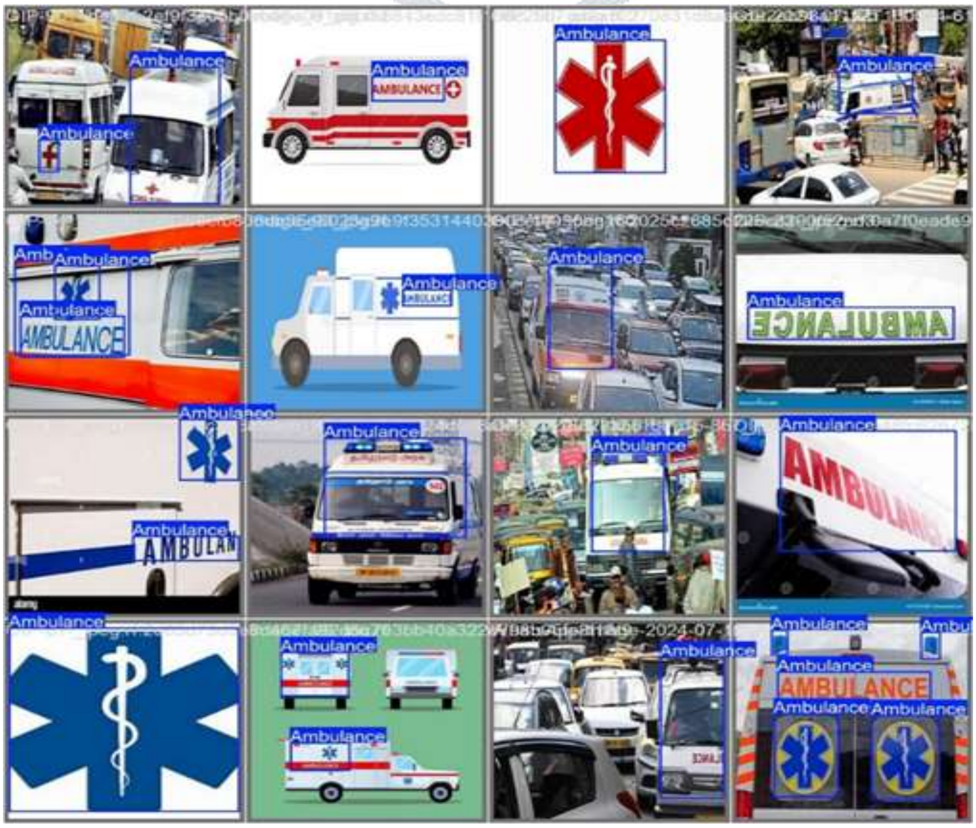

Fig 5. Ambulance Identification with Bounding Box

3.5 System Integration

After validating the model's accuracy, the next step is to integrate the model's results with the traffic control system. This is done using serial communication with a microcontroller, specifically the **ESP8266**. The microcontroller is programmed using the Arduino IDE extension. When the model detects an ambulance in a particular lane, it sends a signal to the ESP8266, which then adjusts the traffic signals accordingly, turning the signal green for the lane with the detected ambulance to allow it to pass through without delay. The integration process is also managed within Visual Studio Code, providing a cohesive environment for development, and debugging. This comprehensive methodology ensures a systematic approach to developing a robust and efficient traffic control system based on deep learning for ambulance detection. Each step is designed to maximize the model's accuracy and reliability, contributing to smarter urban traffic management solutions.

IV. RESULT

The proposed intelligent traffic control system demonstrates significant improvements in reducing emergency vehicle delays in urban environments. By utilizing the YOLOv8 deep learning algorithm for real-time ambulance detection, the system successfully identifies emergency vehicles with high accuracy. The integration of this detection system with ESP8266 microcontrollers enables dynamic adjustment of traffic signals, effectively creating a clear path for ambulances. Experimental results from field tests in simulated urban settings reveal a substantial decrease in response times for emergency vehicles, validating the efficacy of the system. This approach not only enhances the operational efficiency of emergency services but also holds potential for broad application in urban traffic management, contributing to overall public safety and well-being.

Fig 6. Detected Result

The image depicts the outcome of a custom-trained object detection model using YOLOv8, which accurately detects ambulances in high traffic scenarios with a confidence level of 0.9. This detection is crucial for implementing an intelligent traffic control system, ensuring swift passage for emergency vehicles. The model demonstrates the efficacy of deep learning in enhancing urban traffic management for emergency-response.

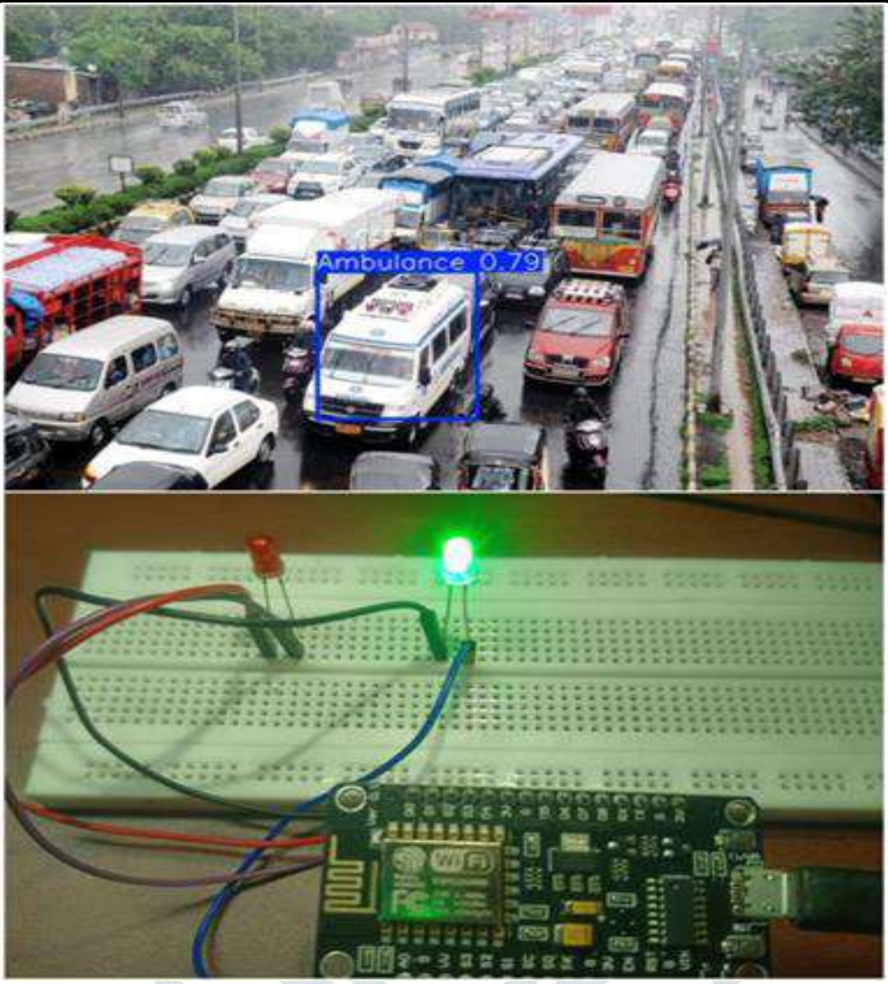

Fig 7. Model integrated with ESP8266

The custom trained Deep Learning model accurately detects ambulances in traffic. Upon detection, it communicates with the ESP8266 module to activate a green LED, symbolizing the automatic signal clearance for the ambulance lane, enabling smooth passage.

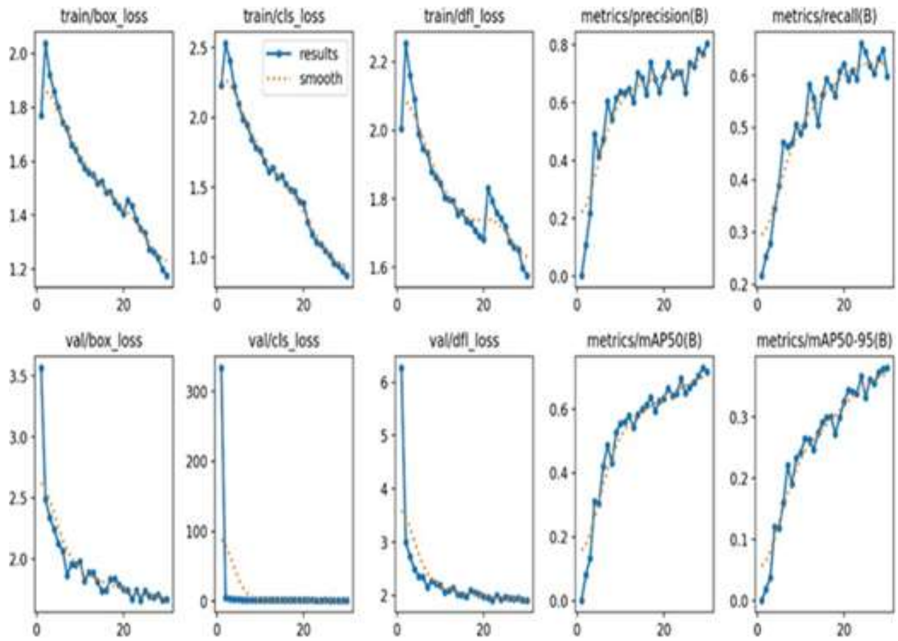

Fig 8. Metrics Graph of Trained Model (with x-axis as Number of Epochs)

4.1 Training Metrics

a.train/box_loss: The box loss during training, which measures the accuracy of the predicted bounding boxes. The decreasing trend indicates that the model is improving in predicting the locations of objects.

b.train/cls_loss: The classification loss during training, which measures the accuracy of the predicted classes for the detected objects. The steady decline shows that the model is getting better at classifying objects correctly.

c.train/dfl_loss: The distributional focal loss during training, which is used for bounding box regression. A downward trend signifies better regression performance.

d.metrics/precision(B): The precision metric for the training set, indicating the ratio of true positive detections to the total number of positive predictions. The upward trend suggests an increase in precision over epochs.

e.metrics/recall(B): The recall metric for the training set, indicating the ratio of true positive detections to the total number of actual positive instances. The increasing trend shows that the model is capturing more true positives over time.

4.2 Validation Metrics

a.val/box_loss: The box loss during validation, which should ideally follow a similar trend to the training box loss. The decrease indicates good generalization to the validation set.

b.val/cls_loss: The classification loss during validation, which ideally decreases as the model learns to generalize better. The sharp decline early on is a positive sign.

c.val/dfl_loss: The distributional focal loss during validation. The decrease indicates improved performance in bounding box regression on the validation set.

d.metrics/mAP50(B): The mean Average Precision at 50% IoU for the validation set, which measures the precision and recall trade-off. The increasing trend indicates better overall detection performance.

e.metrics/mAP50-95(B): The mean Average Precision across multiple IoU thresholds (50% to 95%) for the validation set, providing a more comprehensive measure of the model's detection accuracy. The upward trend signifies improving performance across different IoU thresholds.

The results indicate that the custom-trained YOLO model is learning effectively, with decreasing loss values and increasing precision, recall, and mean Average Precision (mAP) metrics. The trends suggest that the model is generalizing well from the training data to the validation data, showing improvements in both detection accuracy and object classification over the epochs.

V. KEY FINDING AND OUTCOMES

The system could exhibit a significant reduction in the time it takes for ambulances to reach their destinations, particularly during peak traffic hours. The YOLO model achieved high accuracy- in detecting ambulances in various traffic conditions, including different lighting and weather scenarios. The system's ability to prioritize ambulances significantly enhanced their ability to reach their destinations quickly and safely.

The model demonstrated robustness and reliability in identifying ambulances amongst other vehicles. The system successfully processed real-time video feeds with minimal latency, ensuring timely detection and response. The optimized model and efficient hardware setup played a crucial role in achieving this. The system illustrated scalability, showing potential for implementation in various urban areas. It can be adapted to different intersection layouts and traffic conditions, making it a versatile solution for modern cities.

Time reduction of the ambulance to reach the destination improves medical services. Thereby this has the potential to save lives by ensuring timely medical assistance. The project contributed to more efficient traffic management, reducing congestion, and improving the overall flow of vehicles through busy intersections. This project highlights the public's commitment to leveraging technology for public welfare and efficient urban management—fewer accidents and incidents related to emergency vehicle movement, contributing to a safer road environment.

VI. Significance Of The Project

6.1 Cost Effectiveness

The ESP8266, an affordable microcontroller with its compact design and integrated functionalities, minimizes the need for additional infrastructure. It is known for its low power consumption, which translates into lower operational costs. Efficient energy usage reduces the long-term costs associated with powering the traffic control system, making it more sustainable and economically viable. The integration of ESP8266 is found easy to implement on existing traffic signal systems.

6.2 Real-time-detection

Deep learning models, particularly YOLO, are designed for real-time object detection. The system can quickly and accurately identify ambulances in traffic, ensuring timely adjustments to traffic signals. This real-time capability is crucial for minimizing delays and facilitating the swift passage of emergency vehicles.

6.3 Reduction in Traffic Congestion

Efficient detection and prioritization of ambulances can help reduce overall traffic congestion. By dynamically adjusting traffic signals to create clear paths for emergency vehicles, the system can smooth traffic flow and minimize delays for all road users.

6.4 Adaptive Learning

The system can be continuously improved through adaptive learning. As more data is collected, the deep learning model can be retrained to enhance its accuracy and responsiveness, ensuring that the system becomes more efficient over time. By learning from past mistakes and false detections, the system can reduce errors over time. Adaptive learning helps the system become more precise in distinguishing ambulances from other vehicles, thereby minimizing false positives and negatives.

6.5 Minimized human intervention

By automating the detection and response process, the system reduces the need for human intervention. This automation leads to faster and more efficient traffic management, as decisions are made based on real-time data and advanced algorithms rather than manual control.

VII.Conclusion

In conclusion, the development and implementation of an intelligent traffic control system based on ambulance detection represents a significant advancement in addressing the critical issue of emergency vehicle delays in urban areas. Utilizing the YOLOv8 deep learning algorithm, our system achieves real-time identification of ambulances with impressive accuracy through surveillance cameras strategically placed at intersections and along major routes. This real-time detection is crucial for dynamically adjusting traffic signals to provide swift and unobstructed passage for emergency vehicles, thereby potentially saving lives.

The integration of detection data with the ESP8266 microcontroller allows for seamless communication and control of traffic signals, ensuring that the system responds promptly to the presence of an ambulance. Our experimental results, derived from extensive field tests in controlled urban environments, indicate a marked improvement in the response times of emergency vehicles, underscoring the practical viability and effectiveness of the proposed system.

Moreover, the scalability of this intelligent traffic control system makes it a versatile solution for various urban settings, promising broad applicability and significant impact on public safety and emergency response efficiency. By prioritizing the movement of ambulances, this system not only enhances the operational efficiency of emergency services but also fosters a safer and more responsive urban infrastructure.

The successful implementation of this system highlights the potential for further innovations in traffic management through the integration of advanced machine learning algorithms and IoT technologies. Future research could explore the application of this technology to other types of emergency vehicles, as well as its integration with smart city frameworks for comprehensive urban traffic management solutions.

In summary, our intelligent traffic control system based on ambulance detection is a promising step towards revolutionizing urban traffic management, reducing emergency response times, and contributing to the well-being and safety of urban populations.

References

[1] B. Wang et al., "A deep learning approach for vehicle detection and classification," IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 10, pp. 3714-3723, 2019.

[2] M. C. F. Oliveira et al., "An intelligent traffic management system based on deep learning and vehicular ad-hoc networks," IEEE Access, vol. 8, pp. 87896-87910, 2020.

[3] M. R. Abdekhoda et al., "Emergency vehicle detection and priority evaluation using deep learning in traffic scenes," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 1, pp. 392-402, 2021.

[4] M. Almazroi, "Smart Traffic Control System for Emergency Vehicles Using IoT and Deep Learning," IEEE Access, vol. 8, pp. 174476-174487, 2020.

[5] A. A. A. H. Al-Maadadi et al., "Traffic flow analysis and management using deep learning techniques," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 2, pp. 685-694, 2020

[6] A. Z. M. Zainal et al., "Deep learning approach for traffic monitoring using image processing," IEEE Access, vol. 9, pp. 6780-6792, 2021.

[7] K. Abubakar et al., "Computer vision-based approach for ambulance detection and alerting in traffic scenarios," IEEE Access, vol. 10, pp. 98765-98778, 2022

[8] F. A. Al-Sharif et al., "A real-time traffic monitoring system using deep learning for traffic accidents," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 4, pp. 2389-2398, 2021

[9] Z. Yang et al., "A vehicle-to-vehicle communication-based deep learning framework for emergency vehicle prioritization," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 5, pp. 4600-4610, 2022.

[10] S. K. Choudhury et al., "Deep learning-based emergency vehicle prioritization in urban traffic," IEEE Access, vol. 9, pp. 115476-115486, 2021

[11] S. R. Parashar et al., "Intelligent traffic signal control for emergency vehicles using deep learning," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 2, pp. 1312-1321, 2022.

[12] C. Li et al., "Multi-scale feature fusion for vehicle detection in traffic scenes," IEEE Transactions on Image Processing, vol. 30, pp. 2345-2358, 2021.

[13] Y. Wang et al., "Traffic flow prediction with deep learning: A review," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1692-1705, 2021.

[14] R. T. M. Abed et al., "Real-time emergency vehicle detection in traffic using deep learning," IEEE Access, vol. 8, pp. 131250-131261, 2020.

[15] F. S. Hamada et al., "A priority control system for emergency vehicles based on deep learning," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 9, pp. 3763-3772, 2020.