Ambulance Detection and Priority Passage at Urban Intersections Using Transfer Learning and Explainable AI

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***Abstract*—Static traffic signal timings often cause severe delays for emergency vehicles, including ambulances at junctions in urban areas, putting lives at risk. To highlight this, the present study proposes an intelligent traffic control system that dynamically adjusts traffic signals based on real-time monitoring. The system employs a yolov8-based deep learning model fine-tuned through transfer learning for ambulance detection from live video. At an Intersection over Union (IoU) threshold of 0.5, the model achieves a mean Average Precision (mAP) of 0.860. To ensure continuous tracking, NORFair tracking is implemented to ensure constant detection across frames. Additionally, to improve explainability and, the frame incorporates Local Interpretable Model-Agnostic Explanation (LIME), providing visual signals into the model decision-making process. Once an ambulance is detected, the system instantly triggers a green-light activation for the ambulance's lane, enabling quick emergency response. Unlike conventional systems with fixed signal timing, this approach enables smart and adaptive traffic management in urban environment. However, the system's shortcomings in low-visibility situations, such as at night or in fog, despite its encouraging results, highlight the need for incorporating images taken at night and in foggy weather into the dataset**.

Keywords*—Ambulance detection; YOLOV8; LIME; transfer learning; NorFair; urban area; traffic control; smart traffic management

I. Introduction

An efficient emergency response is crucial for saving lives, especially in developing countries where road networks struggle to keep pace with the increasing number of vehicles. Emergency response, which includes ambulances [1] and bikes [2], often faces significant delays due to heavy traffic congestion, particularly at intersections. Traditional traffic management systems operate on pre-installed cycles, failing to dynamically adapt to real-time emergencies, which minimizes response times and hinders the traversal of ambulances through intersections. As the number of vehicles increases by a million every decade [3], it has become a concern for many researchers to provide quality traffic management, particularly for ambulances, to mitigate response times for emergencies.

Consequently, Machine learning and computer vision have unexpectedly enhanced intelligent systems, such as object detection [4], object tracking [5], vehicle counting [6], and traffic light detection [7]. Similar to detection and identification, computer vision algorithms have been adopted to calculate the vehicle speed [8] and pollution monitoring [9]. Furthermore, Machine learning algorithms are employed to control the path following of unmanned vehicles [10], robot navigation [11], and adaptive signal control [12]. While Deep learning models such as YOLO (You Only Look Once) [13] and R-CNN (Region-Based Convolutional Neural Networks) [14] have been effectively utilized for object detection, including the identification of emergency vehicles [15], adapting audio based location of vehicle [16]. Existing research primarily focuses on detection rather than integrating this detection into real-time, dynamic traffic control decision. Most prior studies lack the ability to autonomously manipulate traffic signals in response to ambulance localization, resulting in delayed emergency response and inefficient intersection management. Furthermore, explainable AI techniques have rarely been employed to interpret or validate the model's decision-making process in such safety-critical applications

The primary study of this article is based on an AI-driven traffic signal optimization framework that dynamically modifies vehicle routes upon detecting an approaching ambulance. The method adopted involves leveraging the LIME technique to enhance the confidentiality of the localization system while incorporating the tracking technique to improve traversal through the intersection. The core of this research lies in adopting a tailored object localization model, Yolov8, as a transfer learning approach. The model demonstrates outstanding performance, achieving a mean average precision of 0.85 at the threshold of 0.5. To improve signal optimization beyond vehicle detection, tracking helps monitor the vehicle's trajectory and movement over time. Fig. 1 illustrates the overall system flow.

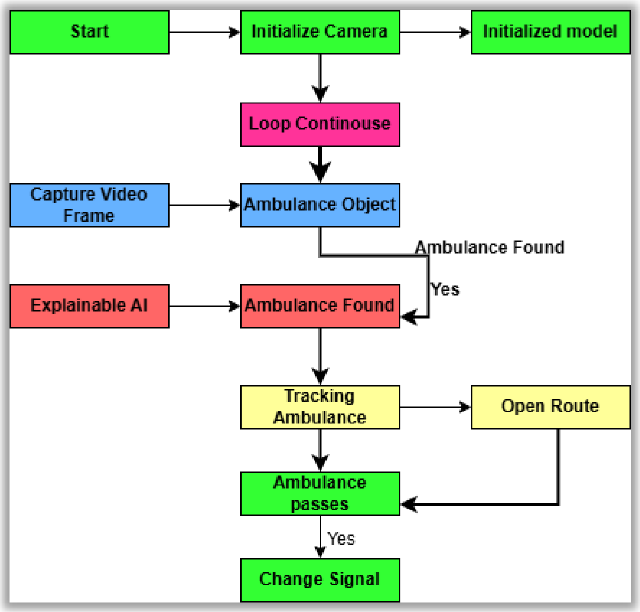

Fig. 1. The flow of the system.

The article presents a novel approach to improving ambulance localization explainability for optimizing ambulance traversal. The contribution of this article can be summarized as follows.

1) Model modification and adaptation: A customized Yolov8 model was used for ambulance detection in a dynamic and active environment using transfer learning, offering robust accuracy and efficiency. Formerly, the model was customized for object localization to support navigation for visually impaired people. This deliberate modification is intended to reduce the parameter, making the model effective for operation, even for a small dataset.

2) LIME for explainability: A significant novelty of this work is the amalgamation of LIME (Local Interpretable Model-Agnostic Explanation) [17] to provide understanding into the model's decision-making process. Integrating LIME into the localization model's prediction, we were able to understand and explain the spatial regions of the image that meaningfully influenced the model's decision to categorize an object as an ambulance.

3) Model transparency: We discussed the black-box nature of the deep learning model by applying LIME [17], making the localization model's predictions more understandable. The LIME explanations discovered which specific visual features helped the model's detection of an ambulance, offering transparency into the decision-making process.

4) Validation and real-world scenario: We demonstrate the practical utility of this approach by using the model on real-world video, including complex situations where ambulances are shown partially. This demonstrates the capability of the detection model, combined with LIME, to provide both accurate and explainable results across various conditions, making the approach suitable for deployment in real-world applications.

5) Optimizing the ambulance traversal: Unlike the existing system, which depends on fixed turns. Our approach focuses on enabling autonomous signal manipulation based on emergency or ambulance detection.

Section II of this article presents a literature review, providing a comprehensive examination of prior literature. Section III details the materials & methods, including dataset justification and selection, as well as the adopted methodology and training process. Additionally, Section IV presents the performance evaluation of the proposed framework, outlining the metrics and parameters used to assess its effectiveness. Section V highlights the results derived from the implemented methodology, while Section VI offers a detailed discussion and interpretation of these findings in relation to existing studies. Finally, Section VII concludes the paper with insights and outlines potential future direction for improving system performance under challenging conditions such as low visibility or heavy traffic.

II. Literature Survey

The escalation of traffic congestion in urban areas, particularly in developing countries, has brought significant challenges to the emergency response system [18]. Traditional traffic signal system [19], operates on predefined fixed-time cycles, often failing to adapt dynamically to real-time scenarios, which leads to delays in emergency vehicle transit such as ambulance. While these conventional systems are simple and cost effective, their lack of adaptability makes them unsuitable for modern, high density urban networks where emergency response time is critical.

Previous research highlights the successful application of artificial intelligence and its various branches across diverse fields [20], [21], [22], [23], [24], [25]. In the context of intelligent transport system (ITS) deep learning models have been employed for task such as object localization, classification and traffic pattern prediction,[4], [26]. Among these YOLO (You Only Look Once) [13] and its successive versions have been recognized for their high speed and accuracy in real time object detection. The newest iteration, YOLOv8 [27], suggests enhanced precision and speed, making it suitable for reliable real-time applications in dynamic environments. Likewise, the model is used successfully and precisely for locating emergency vehicles [18], most studies stop at detection and don't address how this information can be used to actively manage to manipulate traffic signals in response. This limited their practical impact on improving emergency response time.

To refine ambulance detection, researchers have explored multimodal fusion approach that combines visual data with audio cues [16], such as a siren, enhancing detection accuracy under diverse environmental conditions. Furthermore, a hybrid system utilizing an LSTM network for audio signal processing and a ResNet-18 for visual data was suggested [27] have demonstrated higher localization accuracy under noisy or low visibility conditions. These models, however, are often computationally expensive and difficult to deploy in real-time citywide traffic systems, especially in developing regions, where hardware resources are limited.

In addition to advancements in detection and tracking, the nature of deep learning models still raises concerns about the decision-making processes they employ which limit trust and interpretability in safety critical applications such as emergency response. To mitigate this, Explainable Artificial Intelligence (XAI) techniques, such as LIME [28], Grad-CAM [29], have been proposed to make model decision more interpretable. Recent studies have applied XAI in traffic signal optimization [30]. Allowing engineers to better understand and validate model decisions. However, most of these approaches remain experimental and have not yet been integrated into end-to-end real-time ambulance detection.

Results from integrating XAI approaches into traffic management systems have been encouraging [31]. Existing research still lacks a unified framework that combines all the real-time ambulance localization, tracking and interpretable model decisions to dynamically adjust traffic signal. Few studies have attempted to bridge detection and action translating ambulance recognition directly into automated signal manipulation. Addressing this gap, the present study our process focuses on leveraging costumed yolov8 for ambulance localization through transfer learning, incorporating a tracking algorithm for trajectory monitoring, while employing LIME for model Interpretability. This contributes to enhancing emergency response times by ensuring that the traffic signal dynamically adapts to the presence of an ambulance, facilitating their passage through the intersection.

III. Material and Methods

This research article presents an ambulance traversal mechanism through the intersection. The system enhances the dynamic manipulation of the signal by detecting vehicles. Additionally, it provides tracking for monitoring the ambulance's trajectory and LIME for a detailed understanding of why the vehicle was identified as an ambulance.

A. Dataset Overview

To train and evaluate our ambulance traversal system through the intersection, we utilized a publicly available dataset sourced from the Roboflow platform [https://universe.roboflow.com/himank-vpetc/ambulance-4bova/dataset/1]. This dataset was specifically selected for its relevance to real-world situations where the timely localization of vehicles, such as ambulances, is vital for dynamic signal manipulation and the quick passage of ambulances through intersections. The dataset comprises a diverse set of images featuring ambulances in various backgrounds, lighting conditions, and angles, providing robust variability that supports generalization during model training. In addition, the photos are annotated using rectangle bounding boxes that label instances of the ambulances, enabling our customized object detection model to learn spatial and visual features for efficient identification.

B. Dataset Specifications

1) *Source*: Roboflow Universe [31]

2) *Category:* Object detection (Single class "Ambulance")

3) *Number of images:* We used a dataset of 6,432 images, each with dimensions 640 × 640 pixels and 3 color channels, for training the object detection model.

4) *Annotation Format:* YOLO rectangle bounding box

5) *Image Resolution:* The images were down sampled and standardized to a resolution of 640 × 640 pixels

6) *Environment Type:* Urban outdoor scenes, roads

7) *Data Split:* 70% training, 20% validation, 10% test. The approach is employed to gather a balance trade-off between the training and validation performance evaluation and the final test accuracy.

8) Additionally, this uniform split ensures a consistent distribution across subsets, which aids in maintaining a representative sample and preventing overfitting.

C. Justification for Database Selection

The needs of our study, which centered on the real-time detection of ambulances at urban intersections to enable dynamic traffic signal control, led to the selection of the "Ambulance" dataset from Roboflow [31]. This dataset, specifically curated for ambulance recognition, differs from general-purpose object detection datasets in that it offers a focused and domain-relevant collection of annotated images under various real-world scenarios.

The dataset is ideal for training a robust detection model that can operate reliably in live surveillance setups, as ambulances are present in a variety of backgrounds, including junctions, roadside settings, and diverse lighting conditions. Since our suggested solution directly initiates the dynamic reconfiguration of traffic signals to prioritize the passage of emergency vehicles, accurate and timely ambulance recognition is essential.

This dataset aligns well with our research aim, operational, and technical objectives due to its excellent bounding box annotations and conformity to the customized ambulance detection training format. As a result, its applicability and compatibility with real-time, vision-based smart traffic control systems are.

D. Model Architecture and Training Process

1) *Model selection and justification:* In this article, we employed customized YOLOv8 architecture previously modified to highlight the challenges associated with limited data availability. To address the constraints posed by small dataset sizes, a deliberate customization was introduced by reducing the convolutional kernel size from the conventional 3×3 to a more compact 2×2 configuration. This systematic manipulation allows the model to analyze minute details more effectively while concurrently reducing the number of learnable parameters, thus mitigating the risk of overfitting and improving generalization performance.

Furthermore, the padding function was modernized to match the reduced kernel size, confirming proper padding and spatial consistency across layers. The customized convolutional layers combined 64 filters with a stride of 2 × 2 and padding of 1, keeping the dimension of the feature maps. Furthermore, the rectified linear unit (ReLU) activation function was used to increase the discriminative power of feature extraction.

This precisely customized layer design aimed to optimize feature representation while preserving model efficiency. Building upon this foundation, the customized yolov8 model was used through transfer learning to fine-tune it on the ambulance detection job.

E. Training Setup

For transfer learning, the model was retrained using an explicit configuration on the openly available ambulance detection dataset to facilitate transfer learning. The input frames were down sampled to 640 × 640 pixels, and the training process was carried out for 50 epochs, applying a CUDA GPU to quicken the process. To conserve formerly learned generic features, the first ten layers of the network were frozen, allowing only the subsequent layers to fine-tune for ambulance-specific localization. To minimize overfitting, Stochastic Gradient Descent (SGD) was employed, utilizing a learning rate of 0.01, a momentum of 0.9, and a weight decay of 0.001. In addition to visual inspection of predicted bounding boxes, the mean Average Precision (mAP) measure on the validation set was used to track model performance during training. Using an Intersection over Union (IoU) criterion of 0.5, the test set's final evaluation yielded encouraging results with a mean Average Precision (mAP) score of 0.85 shown in PR curve, indicating a high intersection ambulance detection ability.

During training, the model's performance on the validation set was continuously monitored using the mean average precision (mAP) metric. In addition, visual inspection of the model's predictions was conducted to qualitatively assess its accuracy. Upon completion of training, the test set was used to evaluate the model's performance using the same metrics as the validation set. Evaluation was performed at an intersection over union (IoU) threshold of 0.5. The trained model achieved an impressive mAP of 0.850, demonstrating its strong object detection capability. The results of the model are shown in Fig. 2.

Fig. 2. Test set.

For the evaluation of our intelligent traffic management system while incorporating real-time ambulance localization, tracking, with explainable AI, for efficient vehicle traversal, the camera continuously captures the video data to locate the ambulances from the intersection point. Capitalizing on the detection model and the Norfair tracker for persistent object localization—even during occlusions or temporary detection losses—the system reliably monitors ambulance movement. Upon detection, the system triggers the simulated traffic signal to transition to green, allowing for smooth passage. In addition to improving transparency, Local Interpretable Model-agnostic Explanations (LIME) produces visual rationales that capture the most influential frame region, which contributes to model classification. Periodic LIME explanations for high-confidence localization depict insight into the decision-making process, while the Norfair tracker maintains robust trajectory estimation by incorporating location across frames. This integration of state-of-the-art localization, persistent tracking, and explainable AI establishes a responsive and trustworthy emergency vehicle priority system for the urban environment shown in Real-time detection of an ambulance (Fig. 3).

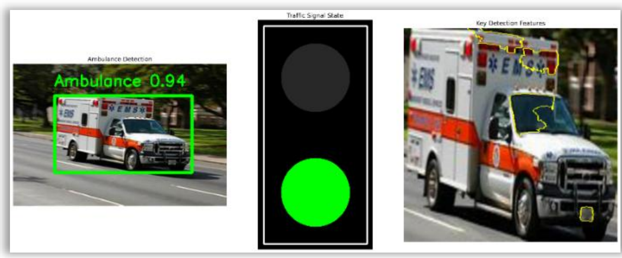

Fig. 3. Real-time detection of an ambulance.

This ambulance passage, combined with ambulance localization, tracker, and LIME, aims to enhance the dynamic management of traffic lights, allowing for reducing response time and improving the traversal of the ambulance through the intersection. The flow of the work is depicted Proposed system architecture (Fig. 4).

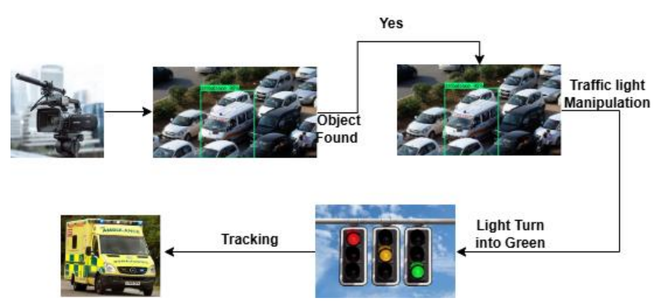

Fig. 4. Proposed system architecture.

IV. Performance Evaluation

To assess the model's effectiveness, the author employed standard performance metrics, namely Precision, Recall, and the F1 score. Precision is the proportion of correctly predicted positive instances to the total predicted positive cases.

Recall is the proportion of correctly identified positive instances to the actual number of positive cases provided to the model.

The formulas for precision and recall are given as:

Precision = True Positive / (True Positive + False Positive) (1)

Recall = True Positive / (True Positive + False Negative) (2)

The F1 score denotes the harmonic mean of precision and recall and is computed by applying the following formula:

F1 Score = (2 × Precision × Recall) / (Precision + Recall) (3)

V. Result

The ambulance detection model used in the current paper was precisely trained on an openly available dataset of ambulance frames captured under diverse environmental conditions, including varying lights, angel and background scenarios. The model exhibited extraordinary performance on this dataset, achieving a mean average precision (mAP) of 0.85 at an IoU threshold of 0.5. This striking result highlights the model's capability to accurately detect ambulances, even in complex urban scenes with background distractions. The consistent bounding box predictions observed during testing further confirm the robustness of the transfer learning approach adopted in this study. Fig. 5 shows PR curve (training result) and Fig. 6 shows the confusion matrix.

A comprehensive analysis of different yolo variants is presented in Table I, summarizing the evaluation of Map, precision, recall and F1 score. While Yolov5 achieved slightly higher precision (0.90) and recall (0.95), our adapted model achieved a balance performance with the highest Map (0.85) and F1 score. This indicates that the proposed model offers an optimal trade-off between precision and recall, meaning it can locate ambulance accurately without significantly increasing false positive or missing detections.

TABLE I. Comparison of Yolo Models

Models	mAP	Precision	Recall	F1-score
YOLOv5	0.84	0.90	0.95	0.84
YOLOv6	0.83	0.89	0.94	0.83
YOLOv7	0.78	0.92	0.94	0.78
YOLOX	0.82	0.86	0.93	0.82
Our Approach	0.85	0.75	0.83	0.85

Object localization serves a pivotal role in computer vision, seeking to divide input images into a grid and predict bounding boxes along with class probabilities for each grid cell. In a typical object detection pipeline, the process commences by segmenting the image into a grid. Each grid cell is then assessed to estimate the bounding box coordinates and the probability that it contains a particular object. Each bounding box prediction consists of four essential coordinates that accurately outline its position within a grid cell. Alongside these coordinates, a confidence score is offered, indicating the likelihood that the predicted box contains an object. This structured approach is a key element of many object localization models, such as YOLOv5 [32], YOLOv6 [33], YOLOv7 [34] and YOLOX [35]. By utilizing this method, these models attain efficient object detection and localization across a broad spectrum of visual environments.

The confusion matrix illustrating the classification performance of our transfer learning model across the ambulance class is shown in Confusion matrix. A relative summary of performance metrics—including mean average precision (mAP), precision, recall, and F1-score—for YOLOv7, YOLOv6, YOLOv5, YOLOX, and our adapted model is given in Table I. The values for precision, recall, and F1-score were derived using the optimal confidence threshold, selected based on the highest F1-score performance.

The slightly lower precision (0.75) compared to other models can be attributed to the model's high sensitivity toward complex backgrounds and reflections, which occasionally resulted in false positives when vehicles had similar color patterns or shapes. However, the high recall value (0.83) indicates that the model effectively identifies almost all ambulance instances in the scene, ensuring minimal missed detections—a critical requirement for emergency response systems. The higher F1-score (0.85) further suggests that our proposed approach achieves a strong balance between detection accuracy and reliability. This performance demonstrates the robustness of the transfer learning strategy employed, confirming that YOLOv8's architectural enhancements contribute significantly to real-time and context-aware ambulance detection, even under dynamically changing urban environments. These findings underline the practical applicability of the proposed system for intelligent traffic management and emergency prioritization.

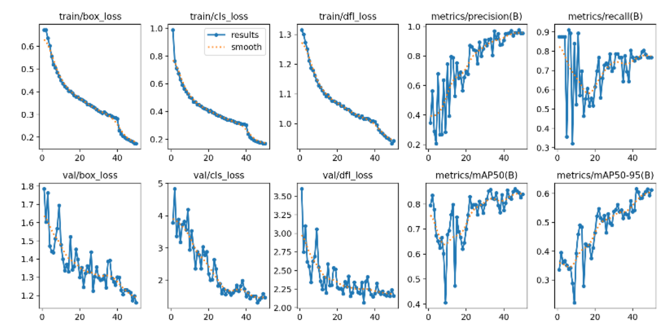

Fig. 5. Training result.

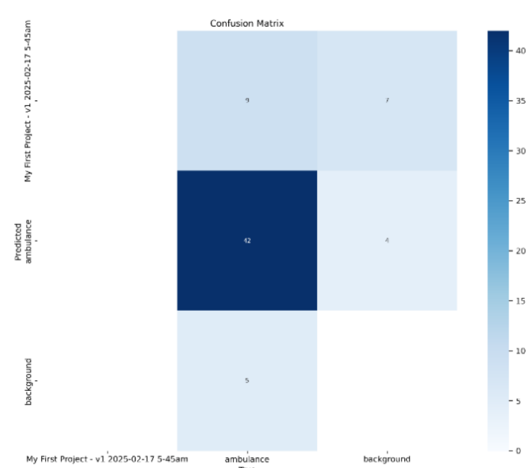

Fig. 6. Confusion matrix.

From a practical standpoint, the proposed system demonstrates substantial potential for real-world implementation within intelligent traffic control frameworks. By accurately identifying and tracking ambulances in real time, the model enables automatic signal adjustment, reducing human dependency and minimizing emergency response delays. The deployment of this system at metropolitan intersections could significantly enhance ambulance traversal efficiency, ensure timely medical assistance and ultimately save lives. Furthermore, its adaptable framework allows integration with existing surveillance infrastructure, making it a cost-effective and scalable solution for developing urban areas (Fig. 7).

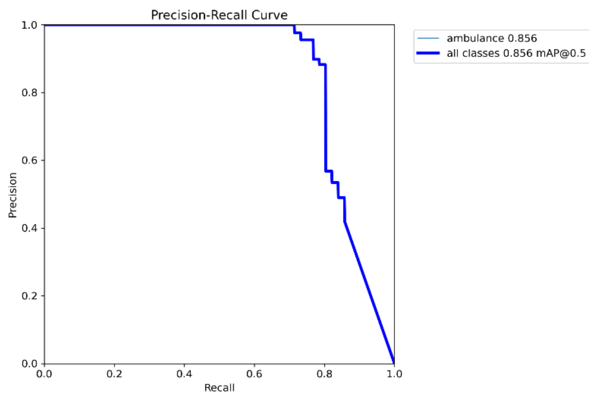

Fig. 7. PR curve.

VI. Discussion

The primary concern of this research article was to introduce a dynamic ambulance traversal system through intersections, particularly in urban areas, by incorporating intelligent traffic signal manipulation based on real-time ambulance detection. The proposed approach leverages a customized YOLOv8 detection model through transfer learning, achieving a mean Average Precision (mAP) of 0.850 show in PR curve at an IoU threshold of 0.5. This performance was optimized by modifying the kernel size to enhance learning on a smaller dataset, thereby improving generalization and reducing overfitting.

Unlike train, addition to traffic management systems that operate on fixed signal timing, our approach enables dynamic control, ensuring immediate clearance of lanes for ambulances upon detection. To track ambulance movement across multiple frames and maintain continuity, NORFair tracking was employed, enhancing the system's temporal awareness and robustness in real-world scenarios. Furthermore, the integration of LIME (Local Interpretable Model-agnostic Explanations) provides visual interpretability by highlighting the features contributing to the model's decision, thereby increasing its transparency and reliability in safety-critical applications.

However, certain limitations persist, including reduced effectiveness during nighttime and foggy weather conditions. These challenges necessitate future research that incorporates thermal imaging and low-light datasets to enhance the reliability of detection. Additionally, the study acknowledges threats to validity, such as dataset bias due to environment-specific data, limited generalization to rural or unstructured settings, and dependency on specific hardware configurations for real-time inference. From a construct validity standpoint, reliance solely on mAP@0.5 as the evaluation metric may not fully capture practical deployment outcomes, highlighting the need for real-world testing and user-centric assessments to validate the system's effectiveness.

Beyond addressing visibility limitations, future work could explore integrating multi-modal sensor fusion (visual, infrared, and audio) to strengthen detection reliability across diverse conditions. Furthermore, extending the framework to multi-intersection coordination through reinforcement learning could optimize city-wide ambulance routing and signal control. Deploying the model on low-power edge devices such as NVIDIA Jetson would further support real-time scalability and facilitate deployment within smart city infrastructures

VII. Conclusion and Future Work

This research article presents a specialized smart traffic signal system designed to ensure the timely and uninterrupted passage of ambulances through urban intersections. The core objective is to overcome the delays commonly experienced by emergency vehicles at traffic signals by dynamically controlling traffic lights in real-time based on ambulance detection. The system integrates advanced computer vision techniques using a custom-trained YOLOv8 model as a transfer learning approach, optimized with a reduced kernel size to enhance performance on a limited dataset. This configuration enables the precise identification of ambulances, even in congested urban environments.

Upon detecting an ambulance, the system immediately manipulates the traffic signals to prioritize the ambulance's lane, ensuring its swift traversal through the intersection. NORFair tracking is employed to maintain continuous monitoring of the ambulance across multiple frames, which is critical for consistent traffic control decisions. Additionally, to enhance the reliability and interpretability of the model, LIME (Local Interpretable Model-Agnostic Explanations) is utilized to visualize and validate the features used for ambulance detection, thereby increasing system transparency.

The proposed solution significantly advances traditional traffic systems, which rely on fixed-timing schedules that often fail to accommodate emergency scenarios. However, while the system demonstrates robust performance during daylight and clear conditions, limitations persist in nighttime or foggy weather, where detection accuracy may degrade. These challenges underscore the need for future enhancements, such as expanding the dataset to encompass diverse lighting and weather conditions and incorporating thermal or infrared imaging to facilitate detection in low-visibility environments.

In addition to enhancing detection under low-visibility conditions, subsequent research could focus on combining multiple sensing modalities, such as visual, infrared, and audio signals, to further strengthen system reliability. Expanding the framework to manage multiple intersections simultaneously and incorporating intelligent learning strategies could allow more efficient city-wide ambulance routes. Finally, implementing the system on compact, real-time edge devices would facilitate practical deployment in smart city environments, ensuring low-latency and scalable performance

Overall, this research contributes to the development of a responsive, intelligent traffic management system that can enhance emergency response efficiency and potentially save lives by minimizing delays at intersections. It lays the groundwork for future smart city infrastructures that prioritize safety and real-time adaptability in urban mobility systems.

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REFERENCES

[1] Rey, W. P., Luyon, J. P. S., Quiros, K. D. A., & Santos, D. B. (2024, March). E-Management Solutions for Ambulance Emergency Response: The Development and Evaluation of Modern E-RA. In Proceedings of the 2024 15th International Conference on E-Education, E-Business, E-Management and E-Learning (pp. 396-404).

[2] Braybrook, P. J., Tohira, H., Brink, D., Finn, J., & Buzzacott, P. L. (2024). Epidemiology and severity of medical events for mountain bikers and hikers transported by ambulance in Western Australia, 2015 to 2020. Wilderness & Environmental Medicine, 35(3), 257-265.

[3] Indrianti, N., Leuveano, R. A. C., Abdul-Rashid, S. H., & Ridho, M. I. (2025). Green Vehicle Routing Problem Optimization for LPG Distribution: Genetic Algorithms for Complex Constraints and Emission Reduction. Sustainability, 17(3), 1144.

[4] He, W., Zhang, Y., Xu, T., An, T., Liang, Y., & Zhang, B. (2025, February). Object detection for medical image analysis: Insights from the RT-DETR model. In Proceedings of the 2025 International Conference on Artificial Intelligence and Computational Intelligence (pp. 415-420).

[5] Wang, J., Wu, Z., Chen, D., Luo, C., Dai, X., Yuan, L., & Jiang, Y. G. (2025). Omnitracker: Unifying visual object tracking by tracking-with-detection. IEEE Transactions on Pattern Analysis and Machine Intelligence.

[6] Lin, C. J., Jeng, S. Y., & Lioa, H. W. (2021). A Real-Time Vehicle Counting, Speed Estimation, and Classification System Based on Virtual Detection Zone and YOLO. Mathematical Problems in Engineering, 2021(1), 1577614.

[7] Huang, Y., & Wang, F. (2025). D-TLDetector: Advancing Traffic Light Detection With a Lightweight Deep Learning Model. IEEE Transactions on Intelligent Transportation Systems.

[8] Lian, H., Li, M., Li, T., Zhang, Y., Shi, Y., Fan, Y., ... & Wu, H. (2025). Vehicle speed measurement method using monocular cameras. Scientific Reports, 15(1), 2755.

[9] Li, M., Tang, Y., Wu, K., & Cheng, H. (2025). Autonomous vehicle pollution monitoring: An innovative solution for policy and environmental management. Transportation Research Part D: Transport and Environment, 139, 104542.

[10] Zhang, J., Yang, M., Chen, Y., Li, H., Chen, N., & Zhang, Y. (2025). Research on sliding mode control for path following in variable speed of unmanned vehicle. Optimization and Engineering, 1-28.

[11] Othman, K., Wang, X., Shalaby, A., & Abdulhai, B. (2025). Integrating Multimodality and Partial Observability Solutions Into Decentralized Multiagent Reinforcement Learning Adaptive Traffic Signal Control. IEEE Open Journal of Intelligent Transportation Systems.

[12] Gallagher, J. E., & Oughton, E. J. (2025). Surveying You Only Look Once (YOLO) multispectral object detection advancements, applications and challenges. IEEE Access.

[13] Veluri, R. C., Khan, S., Sankareswaran, S. P., Shabaz, M., Farouk, A., & Innab, N. (2025). Modified M-RCNN approach for abandoned object detection in public places. Expert Systems, 42(2), e13648.

[14] Ravi, R., & Kanniappan, J. (2025). ZeroEVNet: A multimodal zero-shot learning framework for scalable emergency vehicle detection. Expert Systems with Applications, 275, 126934.

[15] Han, R., Wang, S., Wang, S., Zhang, Z., Chen, J., Lin, S., ... & Pan, J. (2025). Neupan: Direct point robot navigation with end-to-end model-based learning. IEEE Transactions on Robotics.

[16] King, E. A., Tatoglu, A., Iglesias, D., & Matriss, A. (2021). Audio-visual based non-line-of-sight sound source localization: A feasibility study. Applied Acoustics, 171, 107674.

[17] Huang, X., Wang, H., Li, Y., Huang, L., & Zhao, H. (2024). Reservation-based traffic signal control for mixed traffic flow at intersections. Physica A: Statistical Mechanics and its Applications, 633, 129426.

[18] Sarwatt, D. S., Lin, Y., Ding, J., Sun, Y., & Ning, H. (2024). Metaverse for intelligent transportation systems (ITS): A comprehensive review of technologies, applications, implications, challenges and future directions. IEEE Transactions on Intelligent Transportation Systems, 25(7), 6290-6308.

[19] Yin, C., Wang, Z., Li, Y., Sun, K., Wang, S., & Guo, Y. (2025). SBEW-YOLOV8: a small object detection algorithm for autonomous driving based on multi-scale feature fusion. The Journal of Supercomputing, 81(10), 1125.

[20] AlShannaq, F., Alhalawani, S., Al-Jarrah, H., & Shehab, M. (2025, April). Leveraging Deep Learning for Cyberbullying Detection in Arabic Tweets. In 2025 Eighth International Women in Data Science Conference at Prince Sultan University (WiDS PSU) (pp. 134-139). IEEE.

[21] Jaradat, G., Shehab, M., Ibrahim, D., Najdawi, S., & Sihwail, R. (2025). Deep Learning Approaches for Detecting Cyberbullying on Social Media. Journal of Computational and Cognitive Engineering.

[22] Almomani, O., Alsaaidah, A., Abu-Shareha, A. A., Alzaqebah, A., Almaiah, M. A., & Shambour, Q. (2025). Enhance URL Defacement Attack Detection Using Particle Swarm Optimization and Machine Learning. Journal of Computational and Cognitive Engineering.

[23] Alsharaiah, M. A., Abu-Shareha, A. A., Abualhaj, M., Baniata, L. H., Al-saaidah, A., Kharma, Q. M., & Al-Zyoud, M. M. (2024). An innovative network intrusion detection system (NIDS): Hierarchical deep learning model based on Unsw-Nb15 dataset. International Journal of Data & Network Science, 8(2).

[24] Ikram, A., Jalil, M. A., Ngah, A. B., Raza, S., Khan, A. S., Mahmood, Y., ... & Alzayed, A. (2023). Project Assessment in Offshore Software Maintenance Outsourcing Using Deep Extreme Learning Machines. Computers, Materials & Continua, 74(1).

[25] Ikram, A., Jalil, M. A., Ngah, A. B., Sulaiman, A., Akram, M., & Khan, A. S. (2023). Offshore Software Maintenance Outsourcing Process Model Validation: A Case Study Approach. Computers, Materials & Continua, 74(3).

[26] Mecocci, A., & Grassi, C. (2024). RTAIAED: A real-time ambulance in an emergency detector with a pyramidal part-based model composed of MFCCs and YOLOv8. Sensors, 24(7), 2321.

[27] Alruwaili, M., Ali, A., Almutairi, M., Alsahyan, A., & Mohamed, M. (2025). LSTM and ResNet18 for optimized ambulance routing and traffic signal control in emergency situations. Scientific Reports, 15(1), 6011.

[28] Gaspar, D., Silva, P., & Silva, C. (2024). Explainable AI for intrusion detection systems: LIME and SHAP applicability on multi-layer perceptron. IEEE Access, 12, 30164-30175.

[29] Zhang, H., & Ogasawara, K. (2023). Grad-CAM-based explainable artificial intelligence related to medical text processing. Bioengineering, 10(9), 1070.

[30] Ait Ouallane, A., Bakali, A., Bahnasse, A., Broumi, S., & Talea, M. (2022). Fusion of engineering insights and emerging trends: Intelligent urban traffic management system. Information Fusion, 88, 218-248.

[31] Kukartsev, V. V., Ageev, R. A., Borodulin, A. S., Gantimurov, A. P., & Kleshko, I. I. (2024, April). Deep learning for object detection in images development and evaluation of the yolov8 model using ultralytics and roboflow libraries. In Computer Science On-line Conference (pp. 629-637). Cham: Springer Nature Switzerland.

[32] Liu, Y., Lu, B., Peng, J., & Zhang, Z. (2020). Research on the use of YOLOv5 object detection algorithm in mask wearing recognition. World Sci. Res. J, 6(11), 276-284.

[33] Bist, R. B., Subedi, S., Yang, X., & Chai, L. (2023). A novel YOLOv6 object detector for monitoring piling behavior of cage-free laying hens. AgriEngineering, 5(2), 905-923.

[34] Gallo, I., Rehman, A. U., Dehkordi, R. H., Landro, N., La Grassa, R., & Boschetti, M. (2023). Deep object detection of crop weeds: Performance of YOLOv7 on a real case dataset from UAV images. Remote Sensing, 15(2), 539.

[35] He, Q., Xu, A., Ye, Z., Zhou, W., & Cai, T. (2023). Object detection based on lightweight YOLOX for autonomous driving. Sensors, 23(17), 7596.