YOLOv8 Embedded Real Time Traffic Light Adaptation for Enhanced Emergency Vehicle Integration in Autonomous Traffic Management

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***Abstract*—This research introduces a groundbreaking approach to real-time traffic management through the integration of YOLOv8 detection. The system offers immediate traffic light adaptation in response to the presence of emergency vehicles, enhancing overall road safety and traffic efficiency. Leveraging the power of state-of-the-art deep learning, our system dynamically analyzes inputs from multiple cameras, allowing for swift and adaptive adjustments in traffic light states. This novel solution is meticulously evaluated across various emergency scenarios, showcasing unparalleled adaptability and robust decision-making capabilities. The comprehensive examination of diverse emergency situations demonstrates the system's effectiveness in prioritizing emergency vehicle passage while maintaining overall traffic flow. The results highlight the system's significant contributions to intelligent traffic management, positioning it as a pioneering advancement in the realm of smart city initiatives. As urban areas continue to evolve, this study provides a foundation for future research and development in responsive and secure emergency vehicle prioritization. The integration of advanced deep learning technologies in real-time traffic management signifies a transformative shift towards safer and more efficient urban mobility solutions.**

Keywords—object detection, traffic management, decision-making, Emergency vehicle detection

I. Introduction

With urban areas experiencing increased population and escalating vehicular traffic, intelligent and adaptive traffic management systems are crucial [1]. This article introduces an innovative approach that employs YOLOv8 (You Only Look Once version 8), an advanced object detection model [2], to seamlessly integrate real-time adaptive traffic light control, particularly in response to emergency vehicles. Conventional traffic light systems often struggle to respond promptly to dynamic traffic scenarios, especially in the presence of emergency vehicles. This proposed approach addresses this limitation by harnessing the capabilities of YOLO, enabling rapid and accurate detection of emergency vehicles in real-time[3]. By embedding YOLOv8 into the traffic light control system, the model facilitates swift identification of emergency vehicles, triggering adaptive adjustments in traffic light states. Integration into autonomous traffic management ensures a proactive response to emergency situations, mitigating potential risks and enhancing overall traffic safety. This article provides a comprehensive exploration of the proposed system's technical aspects, emphasizing its effectiveness in dynamically changing traffic environments. The study delves into the broader implications of this system within the realm of intelligent transportation systems, aiming to improve traffic flow, reduce congestion, and enhance road safety. Through a detailed examination of the proposed framework, this work contributes to the ongoing discourse on the future of smart transportation and traffic management.

Fig. 1. Emergency Vehicle Collision

Figure 1 visually depicts a collision between two emergency vehicles, illustrating the severity of the crash and emphasizing its significant impact [4].

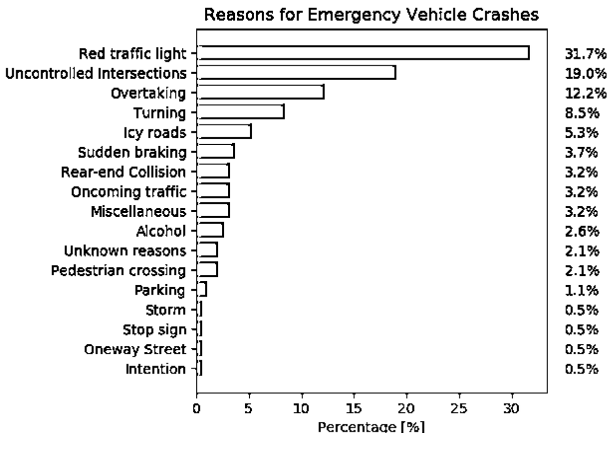

Fig. 2. Collision Causes and Severity

Figure 2 depicts the distribution of collision causes and their associated severity levels, highlighting potential factors that may lead to significant damage.

The decision to study this arises from the alarming statistics, with over 31.7% of emergency vehicle crashes occurring at traffic lights and more than 19% at intersections, as reported in "Modelling green waves for emergency vehicles using connected traffic data" [5]. Some of these incidents result in fatalities and injuries, underscoring the critical need for innovative solutions.

II. RELATED WORKS

Convolutional Neural Networks (CNNs) have emerged as a cornerstone technique, heralded for their unparalleled prowess in discerning intricate patterns essential for identifying emergency vehicles amidst complex environments [6][7]. Pioneering endeavors by Roy and Rahman [8] unveiled a groundbreaking methodology centered around a deep CNN model meticulously crafted to navigate heavily trafficked roadways through the analysis of CCTV footage, offering a transformative perspective on emergency vehicle detection. Similarly, Jaikishore et al. [9] ventured into uncharted territories by leveraging deep learning methodologies tailored to a bespoke dataset, unlocking new vistas for advanced driver assistance systems and fortifying the arsenal of techniques aimed at enhancing emergency response frameworks. Concurrently, the You Only Look Once (YOLO) algorithm has etched its mark in the annals of object recognition, garnering widespread acclaim for its adeptness in discerning emergency vehicles amidst dynamic environments [10]. Noteworthy contributions by Guerrieri and Parla [11] further exemplify the transformative potential of YOLOv3, as evidenced by its seamless integration into mobile vehicle monitoring systems, thus paving the way for automated traffic data measurement. In parallel, Baghel et al. [12][13] embarked on a voyage of refinement, augmenting the capabilities of the YOLO algorithm to enhance emergency vehicle identification and meticulously evaluating the real-time efficiency of their models, thus setting a precedent for meticulous validation in the realm of deep learning-based methodologies. Beyond the realm of CNNs and YOLO, a myriad of alternative strategies have been meticulously scrutinized, ranging from boundary identification and color segmentation to the innovative fusion of hybrid structural frameworks [14]. Notable among these endeavors, Razalli et al. [15] elucidated the potential of HSV color segmentation, while Srinivas et al. [16] charted new frontiers with the employment of edge detection techniques tailored towards enhancing traffic control mechanisms. Meanwhile, the paradigm-shifting proposal by Nellore and Hancke [17] underscored the transformative potential of visual sensing-based traffic control systems, prioritizing the seamless passage of emergency vehicles amidst congested thoroughfares. Further augmenting this discourse, Raman et al. [18] unveiled a meticulously crafted hybrid framework meticulously calibrated to expedite emergency vehicle movement on Indian roads, offering a bespoke solution tailored to the unique challenges posed by diverse urban landscapes. Complementing these pioneering endeavors, Sundar et al. [19] conceived a holistic traffic management system, transcending conventional paradigms to address not only congestion but also proactively facilitating ambulance clearance, thus epitomizing the symbiotic synergy between technological innovation and societal welfare. Moreover, their visionary system incorporates stolen vehicle recognition, further bolstering the resilience and efficacy of emergency response frameworks in safeguarding public safety and well-being. Collectively, these multifaceted endeavors stand as a testament to the dynamic evolution and interdisciplinary nature of emergency vehicle detection research, heralding a new era of transformative solutions poised to redefine the contours of emergency response frameworks on a global scale.

III. DYNAMIC RISK ASSESSMENT

In addressing the intricacies of real-world scenarios, our methodology acknowledges the limitations posed by factors beyond our control, such as unpredictable weather conditions or unforeseen environmental impacts[20][21]. While our model is optimized for the best experimental environment, we recognize that external elements may introduce uncertainties and elevate the level of risk. To account for the inherent unpredictability of uncontrollable factors, we introduce the concept of the Uncontrolled Risk Score.
This metric serves as an indicator of the unknown risks that might arise when confronted with adverse conditions. Symbolized as

$$\text{Risk Score} = \text{Traffic Density} \times \text{Weather Impact}$$

This reflects the potential impact of uncontrolled variables on the overall risk assessment. Uncontrolled Risk Score, our methodology not only emphasizes the importance of adapting to varying environmental conditions but also transparently communicates the presence of unknown risks. This approach ensures a pragmatic understanding of the system's limitations, fostering a holistic view of risk that encompasses both controlled and uncontrollable elements in the dynamic urban landscape. We ais to study only Traffic Density because the weather impact is mostly uncontrollable in the most traffic urbans

IV. METHODOLOGY

A. 4.1 *Traffic Light Control Table*

To provide a clear representation of the system's decision logic, the Traffic Light Control Table takes center stage in our innovative traffic management system. This pivotal table systematically outlines decision logic based on emergency vehicle detection, shedding light on the intricate relationship between designated cameras, emergency vehicle detections, and the resulting states of traffic lights at specific intersections. It serves as a comprehensive tool, elucidating diverse scenarios across various group cases and ensuring an efficient and prioritized traffic management system, particularly for the swift passage of emergency vehicles.

- Camera and Pathway Associations:

T1: Traffic light associated with Camera C1 on pathway P1.

T2: Traffic light associated with Camera C2 on pathway P2.

T3: Traffic light associated with Camera C3 on pathway P3.

T4: Traffic light associated with Camera C4 on pathway P4.

Pathway Intersections: Notably, pathways P1 and P3 form a cohesive route, intersecting with P2 and P4. Similarly, P2 and P4 constitute another interconnected pathway, crossing P1 and P3.

- Pathway Dynamics:

P1 and P3 are in the same pathways but opposite directions and they, crossing P2 and P4 as shown in the figure :

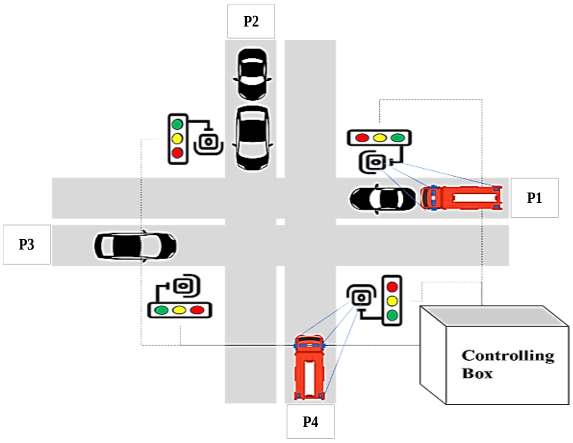

Fig. 3. Detection and control process in interconnected pathways

Figure 3 illustrates the interconnected pathways, each with its camera and traffic light system. These pathways converge at a central controlling box, housing the model and orchestrating system processes. This centralized architecture enables efficient traffic monitoring and control.

- Emergency Vehicle Detection Scenarios:

The table categorizes various emergency vehicle detection scenarios across different group cases, where **1** signifies the presence of one or more **emergency vehicles**.

- Traffic Light States:

- N represents the normal traffic light state
- 1 represents the green light
- 2 represents the yellow light
- 3 represents the red light
- 4 represents the flashing rapidly of yellow and red: This state serves as a distinct alert, signifying a critical emergency scenario. The simultaneous flashing of yellow and red lights indicates a high urgency, ensuring immediate attention and prioritized clearance.

TABLE I. TRAFFIC LIGHT STATES OBSERVED BY MULTIPLE CAMERAS

Case	Cameras				Results			
	C1	*C2*	*C3*	*C4*	*T1*	*T2*	*T3*	*T4*
Case0	*0*	*0*	*0*	*0*	*N*	*N*	*N*	*N*
Case1	*1*	*0*	*0*	*0*	*1*	*3*	*3*	*3*
	0	*1*	*0*	*0*	*3*	*1*	*3*	*3*
	0	*0*	*1*	*0*	*3*	*3*	*1*	*3*
	0	*0*	*0*	*1*	*3*	*3*	*3*	*1*
Case2	*1*	*1*	*0*	*0*	*1*	*4*	*3*	*3*
	0	*1*	*1*	*0*	*3*	*1*	*4*	*3*
	0	*0*	*1*	*1*	*3*	*3*	*1*	*4*
	1	*0*	*0*	*1*	*4*	*3*	*3*	*1*
Case3	*1*	*0*	*1*	*0*	*1*	*3*	*1*	*3*
	0	*1*	*0*	*1*	*3*	*1*	*3*	*1*
Case4	*1*	*1*	*1*	*0*	*1*	*3*	*1*	*3*
	0	*1*	*1*	*1*	*3*	*1*	*3*	*1*
	1	*0*	*1*	*1*	*1*	*3*	*1*	*4*
	1	*1*	*0*	*1*	*4*	*1*	*3*	*1*
Case5	*1*	*1*	*1*	*1*	*1*	*4*	*1*	*4*

Table I presents a comprehensive breakdown of traffic light states observed by multiple cameras in various scenarios. Each case represents a unique combination of camera observations, denoted by the presence or absence of signals from four different cameras (C1, C2, C3, C4). The corresponding results are depicted for traffic lights at four different locations (T1, T2, T3, T4).

B. *Collision Risk Assessment*

In the realm of collision risk assessment within intersections, our methodology is grounded in the precise definition of critical parameters. A key determinant in this evaluation is the calculation of the time required for each detected emergency vehicle to reach the intersection point, expressed by the next formula

$$t_{ev} = \frac{d_{ev}}{S_{ev}}$$

Where t_{ev} represents the time, d_{ev} signifies the distance from the intersection point to the emergency vehicle, and S_{ev} denotes the speed of the emergency vehicle.
To further delve into this temporal assessment, potential collisions are rigorously scrutinized by comparing the times to the intersection for vehicles traversing intersecting pathways[22]. This comprehensive analysis considers a specified range for both speed and distance, ranging from 10 meters to 100 meters and 20 km/h to 60 km/h, respectively. These parameters play a crucial role in ensuring the accuracy and applicability of our collision risk evaluation.
The equation for calculating the probabilities is based on the average time to intersection for emergency vehicles in different configurations within each group case. The equation can be summarized as follows:

$$P(\text{Collision}) = \frac{1}{N}\sum_{i=1}^{N} max\left(0, \min\left(\frac{d_{\text{ev1}}}{S_{\text{ev1}}}, \frac{d_{\text{ev2}}}{S_{\text{ev2}}}, \frac{d_{\text{ev3}}}{S_{\text{ev3}}}, \frac{d_{\text{ev4}}}{S_{\text{ev4}}} - 1\right)\right)$$

Where N is the number of configurations in a group case, $d_{\text{ev1}}, d_{\text{ev2}}, d_{\text{ev3}}, d_{\text{ev4}}$ are the distances to intersection for emergency vehicles 1, 2, 3, and 4, respectively, $S_{\text{ev1}}, S_{\text{ev2}}, S_{\text{ev3}}, S_{\text{ev4}}$ are the speeds of emergency vehicles 1, 2, 3, and 4, respectively, the max function calculates the maximum time to intersection among the emergency vehicles, the min function ensures that the collision probability is between 0 and 1, the outer summation and averaging are performed over all configurations within a group case.

This equation considers that a collision occurs if any of the emergency vehicles arrive at the intersection within the same time step. The probabilities are then averaged over all configurations within each group case.
Integral to our probabilistic assessments are the incorporation of pertinent variables such as relative speeds, individual distances, and the intricate layouts of intersecting pathways. Moreover, our collision probability assessment incorporates a ratio R , $\frac{t_{ev}}{t_{ev'}}$, offering a nuanced perspective that considers the temporal dynamics between different emergency vehicles.

$$R = \frac{t_{ev}}{t_{ev'}}$$

Where t_{ev} represents the time of detection the first emergency vehicles and $t_{ev'}$ represents the time of detecting the next one. This meticulous and scientific approach ensures a robust collision risk evaluation, providing a foundation for informed decision-making within our traffic management system.

C. *Model Training for Emergency Vehicle Detection*

Our approach commences with a meticulous training phase for the YOLOv8 object detection model as shown in the Table. This involves fine-tuning the model on an emergency vehicle annotated image dataset, adjusting class weights, anchor box sizes, and detection thresholds to ensure accurate identification of emergency vehicles.

TABLE II. TRAINING PARAMETERS FOR YOLOV8 OBJECT DETECTION MODEL

Parameter	Value
Task	*Detect*
Mode	*Train*
Model	*yolov8s.pt*
Epochs	*20*
Img_size	*640*
Batch	*8*

Table II showcases the parameters utilized during the meticulous training phase of our YOLOv8 object detection model. The training process involves fine-tuning the model on a dataset annotated specifically for emergency vehicles. Adjustments to class weights, anchor box sizes, and detection thresholds are made to enhance the accuracy of emergency vehicle identification.

D. *Real-Time Traffic Light Adaptation*

In the realm of real-time traffic light adaptation, our system undergoes a seamless process following the successful integration of the YOLOv8 model. This integration empowers our system to dynamically and instantaneously adjust traffic light states based on the results of emergency vehicle detection. The computation of the new traffic light state is governed by a robust decision-making function, expressed as

$$\text{New Traffic Light State} = f(\text{Emergency Vehicle Detection}, \text{Current Traffic Light State})$$

This function is carefully tailored to accommodate diverse emergency vehicle scenarios, ensuring precise and situation-specific adjustments. Crucial to this adaptation process is the integration of safety calculation, a paramount consideration in our methodology. This safety calculation, denoted as

$$Safety = 1 - P_{\text{collision}}$$

encapsulates a comprehensive evaluation of collision probabilities. By considering assumptions related to driver adherence, this safety metric provides a tangible representation of the system's reliability and its capacity to ensure safe traffic flow in the presence of emergency vehicles. This intricate real-time adaptation mechanism stands as a testament to our system's responsiveness and adaptability, contributing significantly to its efficacy in mitigating collision risks and facilitating the smooth passage of emergency vehicles through intersections. Our methodology intricately unfolds from model training and risk assessment to real-time adaptation, robustness considerations, and a clear depiction of decision logic through the Traffic Light Control Table, offering a holistic understanding of our system's efficacy in diverse emergency scenarios.

V. INTERSECTION SAFETY ANALYSIS:

The system's robustness is inherently tied to the hardware, where crucial calculations for collision and safety probabilities are computed, ensuring precise decision-making. This meticulous assessment, detailed in the following Table III, accounts for a spectrum of speeds ranging from 20 km/h to 60 km/h and distances spanning 10 to 100 meters for emergency vehicles approaching intersections. This comprehensive approach underscores the system's commitment to accuracy and reliability.

TABLE III. COLLISION RISK ASSESSMENT FOR EMERGENCY VEHICLES APPROACHING INTERSECTIONS

Case	Pathway Combination	Collision Probability ($P_{\text{collision}}$)	Safety
0	*-*	*0 (No emergency vehicles)*	*1*
1.1	*P1*	*0*	*1*
1.2	*P2*	*0*	*1*
1.3	*P3*	*0*	*1*
1.4	*P4*	*0*	*1*
2.1	*P1 and P2*	*0.69*	*0.31*
2.2	*P2 and P3*	*0.69*	*0.31*
2.3	*P3 and P4*	*0.69*	*0.31*
2.4	*P4 and P1*	*0.69*	*0.31*
3.1	*P1 and P3*	*0*	*1*
3.2	*P2 and P4*	*0*	*1*
4.1	*P1, P2, and P3*	*0.82*	*0.18*
4.2	*P2, P3, and P4*	*0.82*	*0.18*
4.3	*P3, P4, and P1*	*0.82*	*0.18*
4.4	*P4, P1, and P2*	*0.82*	*0.18*
5.1	*P1, P2, P3, and P4*	*0.88*	*0.11*

This table presents collision probabilities ($P_{\text{collision}}$) and safety assessments for various pathway combinations of emergency vehicles approaching intersections. Each row corresponds to a specific pathway combination, detailing the collision probability and safety level. The safety levels range from 0 (High Risk) to 1 (Low Risk). Overall Average of Global Safety is:

- Average ($P_{\text{collision}}$)= 0.4325
- Average ($Safety$) = (1 - Average ($P_{\text{collision}}$) = 0.5675)

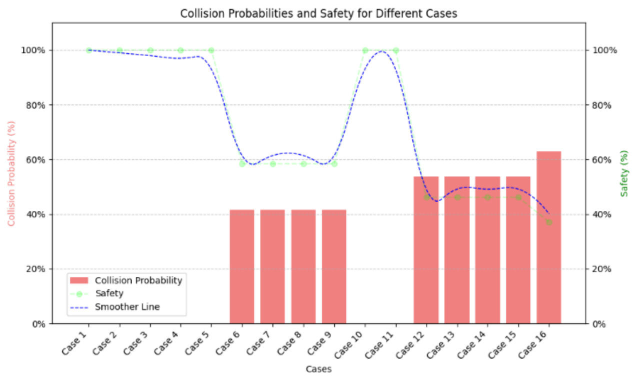

Fig. 4. Collision probability and safety levels across different cases

Figure 4 presents a graph illustrating collision probability and safety levels across different cases.

VI. RESULTS & DISCUSSION

In this comprehensive study, our focus delves into the evaluation of the YOLOv8 object detection model, a pinnacle in real-time detection systems. Our investigation extends beyond mere comparison, as we delve into the intricacies of YOLOv8's performance within a meticulously curated dataset. This dataset is purposefully crafted to enhance the recognition of critical elements, such as emergency vehicles, traffic signs, and medical facility entrances, all with the overarching goal of optimizing traffic management and bolstering safety measures. Our evaluation encompasses a spectrum of performance metrics, including precision, recall, and mean average precision (mAP), setting the stage for an in-depth analysis of YOLOv8's efficacy in real-world applications.

TABLE IV. PERFORMANCE METRICS OF YOLOV8 OBJECT DETECTION MODEL

Class	Precision	Recall	mAP50	mAP50-95)
all	*0.962*	*0.856*	*0.955*	*0.842*
ambulance	*0.959*	*0.754*	*0.927*	*0.788*
fire_truck	*0.978*	*0.842*	*0.945*	*0.804*
police_car	*0.95*	*0.971*	*0.993*	*0.935*

Table IV presents the performance metrics of the YOLOv8 object detection model, providing valuable insights into its effectiveness. The metrics include Recall, Precision, mAP50, and mAP50-95, with respective values of 96.6%, 96.2%, 95.5%, and 84.2%. These metrics collectively demonstrate the model's ability to accurately detect objects while maintaining high precision and consistency across various scenarios.

Fig. 5. Advancing Image Fusion and Detection

Figure 5 showcases the process of detecting and combining images where emergency vehicles are detected. The image represents a specific case studied in the analysis. Additionally, it serves as a testing image output of the YOLO detection system, providing insight into the system's performance.

By enforcing rules that prioritize the safety of emergency vehicles, this adaptive approach holds the promise of significantly reducing collision incidents at intersections. The safety levels range from 0 (high risk) to 1 (low risk) , Overall Average of Global Safety is:

- Average ($P_{\text{collision}}$)= 0
- Average ($Safety$) = 1

Excluding other factors as system errors and weather conditions.

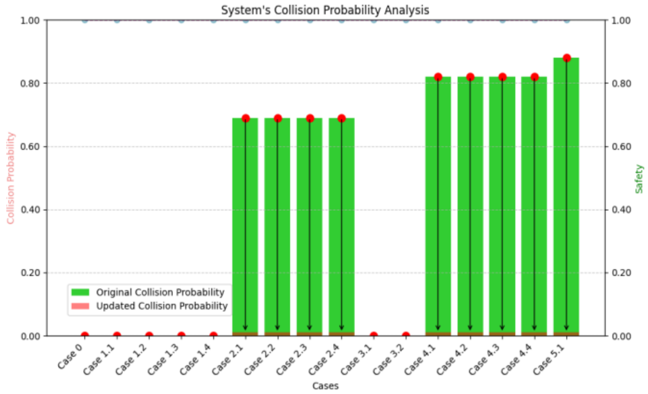

Fig. 6. Collision probability and safety levels across different cases according to the system

Figure 6 presents a graph illustrating safety levels across different cases while the use of the provided system.

This innovative system represents a paradigm shift in traffic management, aiming not only to minimize collision risks but also to optimize traffic flow by proactively adapting traffic light configurations. Looking ahead, the application of similar principles to standard vehicle traffic holds immense potential for enhancing overall road safety and saving lives.

VII. CONCLUSION

In conclusion, our proposed real-time traffic light adaptation system, empowered by YOLOv8 detection, presents a pioneering solution for enhancing traffic management during emergency situations. Through a series of comprehensive experiments and case analyses, we have demonstrated the system's remarkable adaptability and efficiency in responding to varying emergency scenarios. The system excels in providing immediate and coordinated responses when emergency vehicles are detected by one or more cameras. Its ability to dynamically adjust traffic light states ensures a swift and secure passage for emergency vehicles, minimizing response times and potentially saving lives. The multi-case scenarios examined in this study showcase the system's versatility and robust decision-making capabilities. From single-camera detections to complex situations involving multiple cameras across different pathways, our system consistently proves its effectiveness. As we navigate towards a future with increased reliance on intelligent traffic management systems, the presented solution holds immense potential in contributing to safer and more efficient emergency responses. The combination of real-time detection, adaptive decision-making, and coordinated traffic light control positions our system as a valuable asset in urban planning and emergency vehicle prioritization. While the current study provides a strong foundation, future work may delve into additional real-world testing, scalability considerations, and further optimizations. Our system's adaptability and precision make it a promising candidate for integration into smart city infrastructure, offering a glimpse into the potential of artificial intelligence in enhancing emergency vehicle navigation and overall urban safety.

REFS.

[1] R. Ravish and S. R. Swamy, "Intelligent Traffic Management: A review of challenges, solutions, and future perspectives," Transport and Telecommunication, vol. 22, no. 2, pp. 163–182, Apr. 2021, doi: 10.2478/ttj-2021-0013.

[2] J. R. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, "A comprehensive review of YOLO architectures in computer vision: from YOLOV1 to YOLOV8 and YOLO-NAS," Machine Learning and Knowledge Extraction, vol. 5, no. 4, pp. 1680–1716, Nov. 2023, doi: 10.3390/make5040083.

[3] I. Lasri, S. M. Douiri, N. El-Marzouki, A. Riadsolh, and M. Elbelkacemi, "YOLO-Based Approach for Intelligent Apple Crop Health Assessment," in Lecture notes in networks and systems, 2024, pp. 71–77. doi: 10.1007/978-3-031-48573-2_11.

[4] Automatic signal control to prevent emergency vehicle collisions? (n.d.). ITS International. https://www.itsinternational.com/its10/its7/its8/feature/automatic-signal-control-prevent-emergency-vehicle-collisions

[5] Bieker-Walz, L., & Behrisch, M. (2019). Modelling green waves for emergency vehicles using connected traffic data. EPiC Series in Computing. https://doi.org/10.29007/sj1m

[6] Taye, M. M. (2023). Theoretical understanding of convolutional neural network: concepts, architectures, applications, future directions. Computation (Basel), 11(3), 52. https://doi.org/10.3390/computation11030052

[7] A. Omari Alaoui, O. El Bahi, M. R. Fethi, O. Farhaoui, A. El Allaoui, and Y. Farhaoui, "Pre-trained CNNs: Evaluating emergency vehicle image classification," Data & Metadata, vol. 2, p. 153, Dec. 2023, doi: 10.56294/dm2023153.

[8] S. Roy and Md. S. Rahman, "Emergency Vehicle Detection on Heavy Traffic Road from CCTV Footage Using Deep Convolutional Neural Network," in 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), 2019, pp. 1–6. doi: 10.1109/ECACE.2019.8679295.

[9] C. N. Jaikishore et al., "Implementation of deep learning algorithm on a custom dataset for advanced driver assistance systems applications," Applied Sciences, vol. 12, no. 18, p. 8927, Sep. 2022, doi: 10.3390/app12188927.

[10] A. Omari Alaoui, O. El Bahi, M. Oumoulylte, A. El Youssefi, Y. Farhaoui, and A. El Allaoui, "Optimizing Emergency Vehicle Detection for Safer and Smoother Passages," Proceedings of the 6th International Conference on Networking, Intelligent Systems & Security, May 2023, doi: 10.1145/3607720.3607728.

[11] M. Guerrieri and G. Parla, "Deep learning and YOLOV3 systems for automatic traffic data measurement by moving car Observer technique," Infrastructures, vol. 6, no. 9, p. 134, Sep. 2021, doi: 10.3390/infrastructures6090134.

[12] S. Goel, A. Baghel, A. Srivastava, A. Tyagi, and P. Nagrath, "Detection of emergency vehicles using modified Yolo algorithm," in Advances in intelligent systems and computing, 2019, pp. 671–687. doi: 10.1007/978-981-13-8618-3_69.

[13] A. Baghel, A. Srivastava, A. Tyagi, S. Goel, and P. Nagrath, "Analysis of Ex-YOLO Algorithm with Other Real-Time Algorithms for Emergency Vehicle Detection," in Lecture notes in networks and systems, 2020, pp. 607–618. doi: 10.1007/978-981-15-3369-3_45.

[14] R. Harshitha, H. Shetty, B. S. Kavitharani, R. S. Madhura, and M. Jamuna, "Automatic Traffic Management system using YOLO," Social Science Research Network, Jan. 2018, doi: 10.2139/ssrn.3328586.

[15] H. Razalli, R. Ramli, and M. H. Alkawaz, "Emergency Vehicle Recognition and Classification Method Using HSV Color Segmentation," in 2020 16th IEEE International Colloquium on Signal Processing & Its Applications (CSPA), 2020, pp. 284–289. doi: 10.1109/CSPA48992.2020.9068695.

[16] P. Srinivas, "Image Processing Edge Detection Technique used for Traffic Control Problem," 2013. https://api.semanticscholar.org/CorpusID:10603052

[17] N. Kapileswar and G. P. Hancke, "Traffic management for emergency vehicle priority based on visual sensing," Sensors, vol. 16, no. 11, p. 1892, Nov. 2016, doi: 10.3390/s16111892.

[18] A. Raman, S. Kaushik, K. V. S. R. Rao, and M. Moharir, "A Hybrid Framework for Expediting Emergency Vehicle Movement on Indian Roads," in 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), 2020, pp. 459–464. doi: 10.1109/ICIMIA48430.2020.9074933.

[19] R. Sundar, S. Hebbar, and G. Varaprasad, "Implementing intelligent traffic control system for congestion control, ambulance clearance, and stolen vehicle detection," IEEE Sensors Journal, vol. 15, no. 2, pp. 1109–1113, Feb. 2015, doi: 10.1109/jsen.2014.2360288.

[20] I. Pińskwar, A. Choryński, and D. Graczyk, "Good weather for a ride (or not?): how weather conditions impact road accidents — a case study from Wielkopolska (Poland)," International Journal of Biometeorology, Dec. 2023, doi: 10.1007/s00484-023-02592-3.

[21] Y. Zou, Y. Zhang, and K. C. Cheng, "Exploring the impact of climate and extreme weather on fatal traffic accidents," Sustainability, vol. 13, no. 1, p. 390, Jan. 2021, doi: 10.3390/su13010390.

[22] S. Joerer, M. Segata, B. Bloessl, R. Lo Cigno, C. Sommer, and F. Dressler, "A Vehicular networking perspective on estimating vehicle collision probability at intersections," IEEE Transactions on Vehicular Technology, vol. 63, no. 4, pp. 1802–1812, May 2014, doi: 10.1109/tvt.2013.2287343.