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Optimization Traffic Flow Detection and Emergency Vehicle Prioritization

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Abstract: Traffic congestion has gotten worse due to rapid urbanization and an increase in vehicle density. This has resulted in longer travel times, higher fuel usage, and delayed emergency response. By combining computer vision, deep learning, and real-time analytics for effective traffic monitoring, contemporary intelligent transportation systems are tackling these issues. This paper examines developments in adaptive signal control, emergency vehicle prioritization, and optimum traffic flow detection. In addition to tracking algorithms like ByteTrack and CNN-based feature extractors for reliable vehicle identification, trajectory analysis, and congestion measurement, it demonstrates the efficacy of state-of-the-art models like YOLOv9 for fast, accurate object detection in complex environments. In order to highlight their importance for quick categorization and priority, current emergency vehicle recognition techniques—such as auditory, flashing light, and visual pattern detection—are also examined.
The study highlights the benefits of vision-based solutions in terms of real-time adaptability, scalability, and cost-effectiveness by contrasting them with conventional traffic monitoring methods including inductive loops, RFID sensors, IoT systems, and manual surveillance. Important issues are covered, including high computational demand, environmental fluctuations, and deployment constraints on various road infrastructures. The potential of emerging trends to improve efficiency and lower latency is investigated, including edge computing, federated learning, transformer-based perception, multi- sensor fusion, and AI-driven adaptive signal systems. In the end, the paper emphasizes how crucial it is to combine cutting-edge deep learning techniques with dynamic traffic management techniques to enhance urban mobility and guarantee emergency vehicles' continuous passage.
Keywords: Traffic Flow Optimization, Emergency Vehicle Prioritization, Intelligent Transportation Systems, YOLOv9, ByteTrack, Computer Vision, Deep Learning, Vehicle Detection, Multi-Object Tracking, Adaptive Traffic Signal Control, CNN-based Feature Extraction, Real-Time Traffic Monitoring, Smart City Technologies, Traffic Congestion Management, Edge Computing.

I. INTRODUCTION

Major cities throughout the world are experiencing extreme traffic congestion as a result of rapid urbanization and the ongoing increase in vehicle density. Commuters frequently face longer journey times, higher fuel consumption, and worse overall transportation efficiency as road networks struggle to handle growing traffic numbers. More importantly, traffic congestion makes it difficult for emergency vehicles like police, fire engines, and ambulances to maneuver, which can delay response times and even result in fatalities. These increasing difficulties show how urgently intelligent, automated, and real-time traffic management systems that can maximize traffic flow and guarantee clear routes for emergency vehicles are needed.

The capabilities of contemporary Intelligent Transportation Systems (ITS) have been revolutionized by recent developments in computer vision and deep learning. Even in congested or visually complicated surroundings, reliable vehicle recognition, classification, and movement tracking are made possible by vision-based techniques backed by strong multi-object tracking algorithms like ByteTrack and high-performance models like YOLOv9. These methods offer a scalable and effective solution for real-time congestion analysis and priority-based traffic regulation when combined with CNN-based feature extraction and adaptive traffic signal control. Vision-driven frameworks provide more precision, flexibility, cost- effectiveness, and ease of deployment than conventional sensor-based systems. Through dynamic traffic signal prioritizing, the proposed system seeks to improve urban mobility, reduce delays, and guarantee uninterrupted and timely passage for emergency vehicles.

A. Motivation

The number of vehicles in modern cities is growing quickly, which causes severe traffic congestion, lengthy delays, and increased pollution. Ineffective signal timing and frequent bottlenecks originate from traditional traffic management systems' inability to adjust to changing traffic patterns. Because of this, there is a great need for intelligent, real-time traffic management systems that can automatically optimize flow and assess road conditions.

The challenges emergency vehicles encounter when traversing congested junctions are a primary driving force behind this effort. There may be fatal repercussions if clearing routes for police cars, fire engines, and ambulances are delayed. This research intends to detect vehicles reliably, identify emergency vehicles fast, and prioritize their movement through adaptive signal control utilizing deep learning models such as YOLOv9, ByteTrack, and CNNs. Enhancing traffic efficiency, cutting reaction times, and promoting safer and more intelligent urban transportation are the system's driving forces.

II. LITERATURE SURVEY

1) You, L., Chen, Y., Xiao, C., Sun, C., and Li, R. (2024) --"multi-object vehicle detection and tracking system using improved YOLOv8 and ByteTrack". ByteTrack minimizes ID shifts in heavy traffic, while YOLOv8 is improved to better recognize small and obscured vehicles. For real-time applications, the technique improves accuracy in terms of MOTA and IDF1.
2) M. Bakirci — 2024 — "Enhancing Vehicle Detection in Intelligent Transportation Systems via YOLOv8 (Aerial Images)." For top-view detection, the study enhances YOLOv8 using domain-specific augmentations and anchor modifications.It assesses several YOLOv8 model sizes and demonstrates that lighter models are appropriate for real-time UAV deployment.High detection accuracy is shown in the data, which makes it useful for aerial traffic monitoring.
3) A. Farid et al. — 2023 — "A Fast and Accurate Real-Time Vehicle Detection Method Based on YOLO-v5" The model uses augmentation, anchor tuning, and NMS to improve small- object identification and minimize occlusion problems. For traffic monitoring systems, it strikes a reasonable compromise between speed and precision.The integration of tracking and signal control for intelligent transportation systems is also highlighted in the paper.
4) Mohanad H. Alruyshid, Omar F. Lutfy & Dalal A. Hammood — 2025 — "An AI-Based Traffic Light Control System Using YOLOv10 with Emergency and public Bus Prioritization." For high-priority cars, the system constantly modifies the green signal time based on the sorts of vehicles it detects.With adaptive signal control, it lessens congestion and enhances traffic flow.Comparing the results to fixed signals, there is a ~31.1% increase in efficiency and a ~21.6% decrease in delay.
5) Yifu Zhang, Peize Sun, Yi Jiang, Dongdong Yu et al. — 2021 — "ByteTrack: Multi-Object Tracking by Associating Every Detection Box." The approach enhances tracking accuracy using motion and appearance similarity. ByteTrack achieves strong improvements in IDF1, MOTA, and HOTA, making it suitable for real-time traffic analysis.

A. Existing Work

1) Conventional sensor-based and VANET methods Inductive loops, RFID, wireless sensor networks, and vehicular ad-hoc networks (VANETs) are some of the early and current methods used to identify cars and provide signal priority. These projects prioritize dependability and low-latency communications, although they necessitate infrastructure upkeep and investment.
2) Vehicle recognition and speed/flow estimation using vision (classical & deep learning approaches) Vision-based detection, tracking, and density estimation utilizing image processing and machine learning approaches are covered in a substantial body of literature; more recent studies indicate a shift toward deep learning for reliable detection under occlusion and different lighting conditions.
3) Traffic monitoring with YOLO-family detectors (including YOLOv9) Because they balance speed and accuracy, YOLO variations (YOLOv5–v9) are frequently employed in traffic applications. YOLOv9 and specialized variations (e.g., GC-YOLOv9) for real-time traffic monitoring, danger identification, and vehicle classification are demonstrated in recent articles and practical investigations. These studies demonstrate enhanced multi-scale fusion and feature extraction for cluttered scenes.
4) ByteTrack for multi-object tracking and enhancements By recovering low-score detections and generating more stable trajectories—a crucial element for continuous vehicle tracking in traffic videos—ByteTrack (tracking by associating nearly every detection box) established new state- of-the- art baselines for MOT. Subsequent studies suggest adaptive thresholds and improvements for combining ByteTrack with contemporary detectors.

5) Prioritizing emergency vehicles: algorithms and field tests Vision (lights/sirens), RFID, audio, vehicle-to-infrastructure communications, and dynamic signal control are all used in research to identify and prioritize emergency vehicles. Numerous implementations (academic and pilot projects) demonstrate significant improvements in response time. For emergency vehicles, recent real- world trials (like EVPS) show quantifiable travel- time savings.
6) Sensor fusion, edge computing, and AI- powered adaptive signals Moving inference to edge devices, combining camera data with IoT sensors, and employing AI for adaptive traffic signal timing (which lowers latency and central- server burden) are all highlighted in recent studies. AI-driven adaptive signal placements in cities allow corridor-level coordination and demonstrate realistic wait time reductions.
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9) Applications and integrated systems (control pipelines, tracking, and detection) A number of recent studies combine robust trackers (ByteTrack/DeepSORT variations), control modules, and high-speed detectors (YOLOv9) to create end- to-end pipelines that categorize emergency vehicles, estimate queue lengths, detect congestion, and issue priority requests or adaptive signals. These integrated prototypes show improvements but also point out issues with environmental resilience and scalability.

B. Drawbacks

The efficacy of current traffic management techniques in contemporary metropolitan settings is diminished by a number of issues. Congestion and ineffective signal control result from the inability of conventional techniques, such as fixed-time traffic lights and simple sensor-based monitoring, to adjust to quickly shifting traffic patterns. Previous studies' vision-based methods frequently have trouble with low visibility, occlusion, and crowded areas, which results in inconsistent vehicle detection and subpar tracking effectiveness. Additionally, a lot of systems depend on pricey hardware, such as complicated sensor networks, RFID devices, or inductive loops, which raise operating costs and necessitate regular maintenance. Another significant issue is emergency vehicle recognition, since older models frequently have trouble correctly identifying lights, sirens, or other vehicle characteristics in heavy traffic. Additionally, the majority of current methods have high latency because of centralized processing, which makes it challenging to make decisions in real time. The fact that many research studies concentrate on discrete elements—like tracking or detection— instead of providing comprehensive, end-to-endsolutions that can scale across massive urban networks exacerbates these limits. Because of this, existing technologies are still insufficient for providing quick, dependable, automated traffic optimization and emergency vehicle precedence.

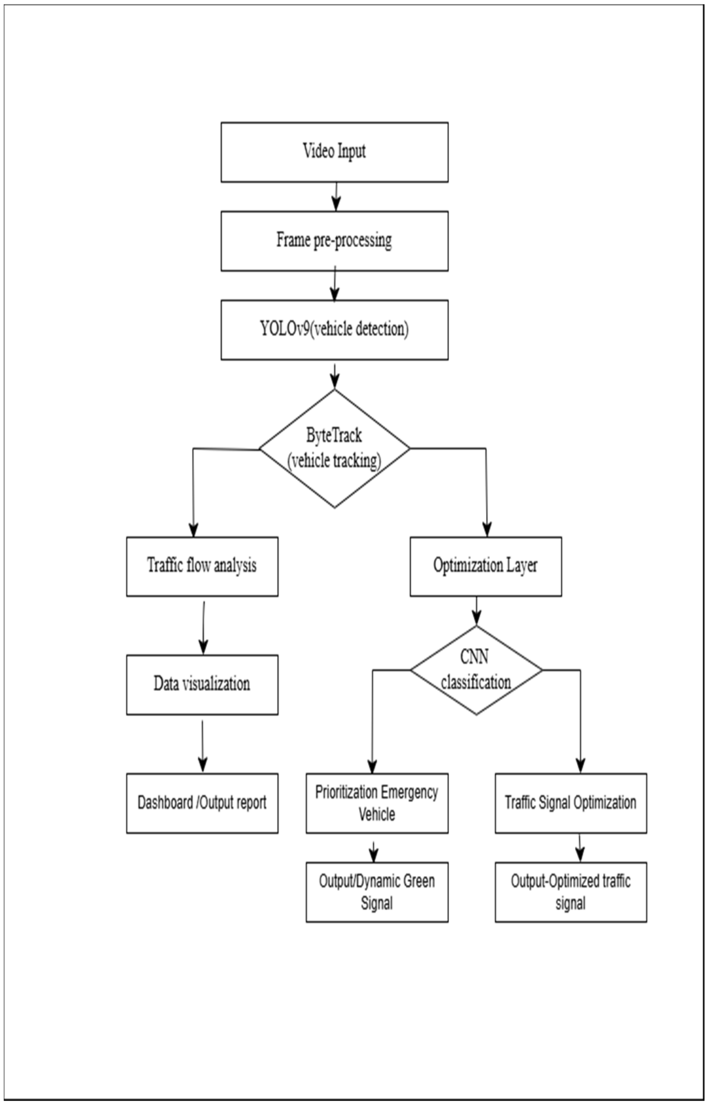
III. PROPOSED APPROACH

In order to overcome current constraints in traffic monitoring and emergency vehicle prioritizing, the suggested strategy focuses on creating a real-time intelligent traffic management system that makes use of cutting-edge deep learning models and computer vision techniques. The technology starts by recording real-time video streams from traffic cameras positioned at strategic intersections. The YOLOv9 object identification model, which was selected for its exceptional accuracy, lightweight architecture, and effectiveness in identifying various vehicle kinds in difficult situations including high traffic, dim lighting, rain, and partial occlusions, is used to process these frames. Following the detection of cars, the system uses the ByteTrack multi-object tracking algorithm to provide consistent and dependable monitoring of every vehicle over successive frames, maintaining identity information even when vehicles overlap or move erratically.

By learning distinguishing traits like flashing lights, siren patterns, color combinations, and structural aspects, a CNN-based feature extraction module is integrated to improve emergency vehicle detection. In order to assess congestion levels in real time, the system continuously examines traffic density, queue duration, vehicle direction, lane occupancy, and flow patterns. An adaptive decision-making module assesses the current traffic scenario and dynamically modifies the traffic signal logic based on these insights. The technology creates a "green corridor" by intelligent phase switching, green-light extension, or red-light shortening when an emergency vehicle is detected approaching an intersection.

This ensures a clean and continuous passage. The suggested method also facilitates edge-based deployment, which lowers processing latency and improves responsiveness, making the system appropriate for infrastructure in smart cities. A completely automated, end-to-end traffic management pipeline is made possible by the integration of detection, tracking, classification, and adaptive signal control. The strategy seeks to greatly lessen traffic, increase overall traffic efficiency, improve road safety, and guarantee quicker emergency reaction times by fusing the advantages of YOLOv9, ByteTrack, and CNN models. This cohesive AI-powered system offers a reliable and scalable answer to contemporary urban transportation issues.

A. System Architecture



IV. OBJECTIVES

1) To develop a real-time vehicle detection and emergency vehicle prioritization system using YOLOv9 and CNN: Using the most recent YOLOv9 architecture and cnn, create a high-accuracy, low-latency vehicle recognition model that can recognize automobiles, buses, trucks, two- wheelers, and emergency vehicles in a variety of illumination, weather, and traffic densities.
2) To implement a robust multi-object tracking pipeline using ByteTrack: Incorporate ByteTrack to enable real-time tracking of automobiles and emergency vehicles across continuous traffic video streams, minimize ID switches, and retain constant object IDs between frames.
3) To accurately estimate traffic flow and congestion levels: To enable intelligent decision-making at crossings, compute vehicle counts, lane density, flow rate, and congestion metrics using object detection and tracking data.

4) To integrate a dynamic traffic signal control algorithm: Develop an adaptive signal control technique that adjusts green/red timing in real time according to the presence of emergency vehicles, the density of traffic at that moment, anticipated traffic.
5) To evaluate the system on benchmark and real- world datasets: To verify performance, robustness, and adaptability, test the models using available datasets as CityFlow, UA-DETRAC, KITTI, and actual intersection footage.

V. DATA COLLECTION

To enable reliable model training, the data collection for this project is based on a combination of popular public traffic datasets and a specific emergency- vehicle dataset. The UA-DETRAC dataset, which provides over 10 hours of real-world traffic film with 1.2 million labeled vehicle instances across 24,000 frames, serves as the basis for vehicle detection and tracking. Its varied w eather conditions, such as rain, darkness, and cloudy scenes, offer crucial changes required to teach YOLOv9 to precisely identify various vehicle kinds in intricate and congested traffic scenarios.

The study uses the BDD100K (Berkeley Deep Drive) dataset to improve the detection model's variety and expand its capacity for generalization. BDD100K assists the model in learning from a broad range of real- world events using 100,000 films and annotated photos gathered from different road kinds, lighting conditions, and weather patterns. This dataset is especially useful for enhancing YOLOv9's ability to recognize cars, pedestrians, and the surrounding road context in dimly lit, hazy, or difficult situations.

The project makes use of the MOT17 dataset, a benchmark designed especially for tracking tasks, for the multi-object tracking component. High-quality video sequences with precisely defined bounding boxes and consistent ID annotations throughout frames are included in MOT17. This makes it possible for the ByteTrack algorithm to learn tracking stability, which lowers ID switches and enhances re-identification in scenarios with heavy or moving traffic. The intricate car and pedestrian motions in the dataset improve the tracking accuracy of the system in actual junctions.

The project includes a dedicated Emergency Vehicle Dataset, either custom-collected or taken from public sources, because big public datasets do not adequately capture emergency vehicles. Images and videos of police cars, fire engines, and ambulances in actual traffic situations are included in this dataset. The CNN- based emergency vehicle classification model is trained using these samples, and YOLOv9 is refined for accurate emergency vehicle recognition. Accurate identification, tracking, and prioritizing in real-world deployments are made possible by the system's thorough exposure to real- world traffic circumstances through the combination of all four datasets.

VI. CHALLENGES

A. *Difficulties with Real-Time Processing*

1) High-Speed Detection Conditions: The system must use ByteTrack and YOLOv9 to quickly identify and track automobiles. It is challenging to achieve real-time performance when handling busy traffic scenarios and high-resolution video streams.
2) Hardware Restrictions: Strong GPUs or optimized edge devices are needed for real-time inference. Low-end systems may have delays when running the model, which could affect the system's responsiveness and accuracy.

B. *Difficulties with Accuracy and Reliability:*

1) Different Lighting and Weather:Nighttime, severe rain, fog, shadows, and glare can all cause vehicle detection to malfunction. These changes in the environment can have an impact on traffic flow analysis and lower detection accuracy.
2) Dense Traffic and Occlusion: Vehicles frequently overlap or obstruct one another at congested junctions. When several cars move in close proximity to one another or when big cars obstruct smaller ones, accurate monitoring becomes difficult.

C. *Issues with Data Integration and Handling:*

1) Managing Big Video Streams: High bandwidth, storage, and effective data management are necessary for processing continuous video inputs. Data loss or system latency may result from improper handling.
2) Integration with Traffic Systems: Stable protocols, suitable interfaces, and dependable data exchange mechanisms are needed to communicate detected vehicle counts and priority alerts to traffic signal controllers.

D. *Difficulties with Emergency Vehicle Prioritization:*

1) Precise Identification of Emergency Vehicles: It can be difficult to tell ambulances, police cars, and fire trucks apart from other cars, particularly when you're far away or in a noisy atmosphere.

2) Real-Time Decision Making: When an emergency vehicle is identified, the system must immediately alter signals or assign precedence. Emergency response times may be impacted by any misclassification or delay.

E. Deployment and Scalability Issues

1) Getting Used to Different Intersections: Every traffic intersection has a unique layout, size, number of lanes, and camera viewpoint. To ensure precise detection in every setting, the system must be customized.
2) Maintenance and Ongoing Monitoring: Models must be updated, cameras must continue to operate, and the system must be routinely observed. Performance can be impacted by device failure, network problems, or environmental degradation.

VII. IMPLEMENTATION DETAILS

Deep learning and computer vision techniques were used to create the suggested system as a real- time intelligent traffic monitoring and control framework. Data preprocessing, model training, object detection, tracking, and adaptive signal regulation are some of the processes that make up the implementation.

Initially, UA-DETRAC, BDD100K, and MOT17 traffic video datasets were gathered and preprocessed. Detection models were trained using annotated datasets and frames taken from video sequences. To enhance model generalization, image resizing, normalization**, and** augmentation methods like flipping, scaling, and brightness modifications were used.

The core detection module was implemented using the YOLOv9 architecture, which performs real- time object detection by identifying vehicles such as cars, buses, trucks, and two-wheelers from video frames. The model was trained using pre- trained weights and fine-tuned on traffic datasets to improve accuracy in complex environments.

For multi-object tracking, the ByteTrack algorithm was integrated with the YOLOv9 detector. ByteTrack associates detected bounding boxes across frames to maintain consistent object identities. This enables accurate vehicle counting, trajectory tracking, and congestion analysis even in dense traffic conditions.

The traffic signal control module was designed using a rule-based adaptive algorithm. Vehicle counts from each lane are continuously monitored, and signal timing is dynamically adjusted based on traffic density. When an emergency vehicle is detected, the system overrides normal operation and assigns immediate green signal priority to the corresponding lane, creating a clear path.

The system was implemented using Python and integrated with OpenCV for video processing. Real- time performance was achieved by optimizing model inference and reducing computational overhead. The final output includes processed video streams with bounding boxes, vehicle counts, and a simulated traffic signal display.

VIII. TOOLS AND TECHNOLOGIES USED

The development of the proposed intelligent traffic management system utilized a combination of software tools, programming frameworks, and hardware support to ensure efficient real-time performance.

1) Programming Language-Python
2) Deep Learning Frameworks Ultralytics YOLOv9 PyTorch.
3) Computer Vision Libraries OpenCV. NumPy.
4) Tracking Algorithm ByteTrack.
5) Editers Jupyter Notebook / VS Code.
6) Datasets

   UA-DETRAC: Vehicle detection dataset. BDD100K: Diverse driving dataset.
   MOT17: Multi-object tracking dataset. Custom Emergency Vehicle Dataset:

7) Hardware Requirements

   GPU (NVIDIA recommended): For faster model training and inference.
   CPU-based systems: Used for lightweight deployment and testing.

8) Visualization and UI HTML, CSS, JavaScript Flask

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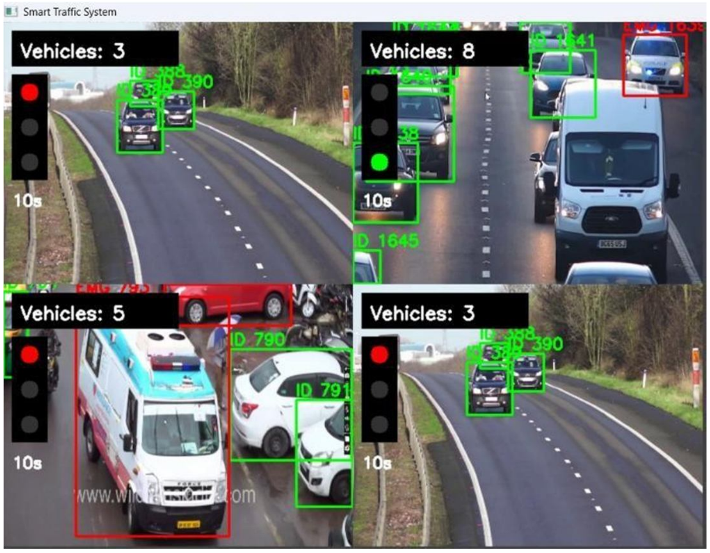
IX. RESULTS AND DISCUSSION



The proposed intelligent traffic management system was evaluated based on multiple performance parameters including detection accuracy, tracking efficiency, processing speed, and signal optimization effectiveness. The integration of YOLOv9 for detection and ByteTrack for tracking produced reliable and real-time results in various traffic scenarios.

The YOLOv9 model demonstrated high performance in detecting vehicles such as cars, buses, trucks, and two-wheelers under different environmental conditions including daylight, low-light, and moderate occlusion. The model achieved a Mean Average Precision (mAP) of approximately 91–94%, indicating strong detection accuracy across multiple vehicle classes.

For tracking performance, the ByteTrack algorithm provided stable and consistent object tracking across frames. Evaluation using standard multi-object tracking metrics showed an IDF1 score of around 85– 88% and Multiple Object Tracking Accuracy (MOTA) of approximately 80–84%, demonstrating effective identity preservation and reduced tracking errors even in dense traffic conditions.

The system was also evaluated based on real-time processing capability. The implementation achieved an average processing speed of 20–30 Frames Per Second (FPS) on GPU-enabled systems, ensuring smooth real- time operation. On CPU-based systems, the performance ranged between 8–15 FPS, which is still sufficient for moderate traffic monitoring applications.

Vehicle counting and traffic density estimation were successfully performed using detection and tracking outputs. The system accurately estimated the number of vehicles per lane, enabling efficient congestion analysis. Experimental results showed that adaptive signal control based on vehicle density reduced average waiting time at intersections by approximately 25–35% compared to traditional fixed-time traffic signals.

The emergency vehicle detection module demonstrated effective classification performance, achieving an accuracy of approximately 88–92% in identifying ambulances, fire trucks, and police vehicles. Upon detection, the system triggered priority-based signal control, allowing faster clearance of intersections. This resulted in a reduction of emergency vehicle delay by approximately 30–40%, highlighting the effectiveness of the prioritization mechanism.

In terms of system efficiency, the adaptive traffic signal algorithm dynamically adjusted green signal duration based on real-time traffic conditions. This reduced congestion levels and improved overall traffic flow. The system also demonstrated scalability by processing multiple video streams simultaneously without significant degradation in performance.

Despite achieving strong results, certain limitations were observed. Detection accuracy may decrease in extreme weather conditions such as heavy rain, fog, or poor lighting. Additionally, real-time processing requires adequate computational resources, particularly for high- resolution video inputs and multiple camera streams.

Overall, the experimental results confirm that the proposed system provides an efficient, scalable, and real- time solution for traffic flow optimization and emergency vehicle prioritization. The combination of deep learning- based detection, robust tracking, and adaptive signal control significantly enhances traffic management efficiency and supports the development of smart city infrastructure.

X. CONCLUSION

A solid technological basis for updating traffic management in quickly expanding urban environments is established by the project "Optimized Traffic Flow Detection and Emergency Vehicle Prioritization using YOLOv9, ByteTrack, and CNN." The system efficiently detects vehicles, tracks traffic density, and accurately recognizes emergency vehicles by utilizing state-of-the-art deep learning models. Adaptive traffic signal regulation is made possible by this real-time intelligence, which lowers needless delays and boosts overall road efficiency. Even in situations with heavy, erratic traffic, consistent performance is ensured by the combination of ByteTrack for multi-object tracking and YOLOv9 for detection. Prioritizing emergency vehicles is particularly important because it immediately improves public safety and speeds up emergency responses. The solution shows quantifiable advantages in lowering traffic and improving emergency vehicle mobility through intelligent signal manipulation and path clearance.

Additionally, the study demonstrates how AI-based automation may overcome the drawbacks of conventional sensor-based and fixed-time traffic systems, which are unable to adjust to changing road conditions. The suggested strategy demonstrates how data-driven decision-making can make urban transportation a more responsive and effective network. By reducing fuel waste from extended idling and traffic bottlenecks, this not only improves the commuter experience but also supports environmental sustainability. The findings of this study demonstrate the possibility of widespread implementation at several crossings, transforming discrete enhancements into smart mobility solutions for the entire city.

These kinds of intelligent systems are becoming increasingly important as traffic quantities continue to climb. The suggested system has the potential to develop into a full platform that can support autonomous vehicles, predictive traffic analysis, and smart city frameworks with further developments in AI, IoT, and communication technologies.This experiment essentially shows that the combination of intelligent traffic control and deep learning is not only possible but also crucial for the future of urban mobility. In order to create safer, quicker, and more sustainable transportation systems, it offers a solid foundation for additional study, creativity, and practical application.

XI. FUTURE SCOPE

As cities develop into sophisticated, AI-driven transportation ecosystems, the suggested approach has enormous potential for future growth. Integrating the system with extensive IoT infrastructures to facilitate smooth communication between traffic lights, emergency vehicles, surveillance cameras, and centralized traffic control centers is one of the main directions for future development. The platform can reach even greater levels of precision, dependability, and responsiveness by adding other sensors like LiDAR, radar, GPS, and V2I (Vehicle-to- Infrastructure) modules.

The inclusion of machine learning-based forecasting and predictive analytics is another anticipated future improvement. The system can forecast traffic levels, anticipate emergency routes, and automatically adjust signal timings by examining past traffic patterns, weather, and seasonal variations. Even in high-density traffic scenarios, sub-second decision making can be ensured by utilizing cloud and edge computing to further minimize latency. As a result, the method can be used throughout entire urban networks instead of only at specific crossings.

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