ADVANCEMENTS IN SMART TRAFFIC FLOW OPTIMIZATION

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Abstract—This paper proposes an Advanced Smart Traffic Management System (ASTMS) leveraging advanced Internet of Things (IoT) sensors, real-time computer vision, and predictive analytics to address urban traffic congestion. This work combines the Kalman Filter and the You Only Look Once (YOLO) algorithm to create a real-time vehicle identification, tracking, and counting system. Utilizing YOLO (You Only Look Once) for real-time vehicle detection and Kalman Filters for predictive traffic light control, the STMS maximizes traffic efficiency and congestion relief. The system applies weather analytics, event-based rerouting, and emergency vehicle priority for enhanced safety and mobility. Long Short-Term Memory (LSTM) networks are utilized to predict traffic patterns for proactive signal control. An easy-to-use mobile app provides real-time traffic status, recommends alternate routes, and incorporates a feedback module for continuous improvement. The proposed initiative advances the Sustainable Development Goals (SDGs) through the promotion of environmentally sustainable traffic management, reduced emissions, and enhanced responsiveness in emergencies. An easy-to-use mobile app provides real-time traffic status, recommends alternate routes, and incorporates a feedback module for continuous improvement. The proposed initiative advances the Sustainable Development Goals (SDGs) through the promotion of environmentally sustainable traffic management, reduced emissions, and enhanced responsiveness in emergencies. The STMS is a major step toward constructing "smart cities with intelligent, adaptive, and sustainable traffic policy."

Keywords: *Sensors, Variable message sign board (VMS), Kalman filter*

I. INTRODUCTION

[1]In modern urban environments, the increasing volume of traffic has become a global issue that requires critical thought. Traffic Community mobility is impacted by congestion, in addition to negatively affecting the air quality, the efficiency of transportation, and traffic safety. According to the World Bank assessment from 2020, Traffic congestion can cost drivers tens of hours of productive time. Annually, leading to significant monetary losses.

Additionally, one of the primary sources of motor vehicle emissions is Greenhouse gas emissions from cities, which worsen climate change and decrease the quality of life in large cities. Beyond just easing traffic jams, Intelligent Transportation Systems (ITS) optimize transportation infrastructure through data-driven decision-making, real-time monitoring, and traffic pattern analysis. An autonomous vehicle monitoring and detection system is a crucial part of ITS that makes traffic control more efficient. These systems are used for a variety of purposes, including traffic signal optimization, road density analysis, traffic infraction detection, and vehicle counting. [2]

Vehicle detection systems find vehicles in each video frame, while tracking ensures that the same vehicle is consistently followed across frames. YOLO is perfect for real-time applications since it just takes one step to process photos or videos. Despite its advantages in terms of speed and accurate detection, YOLO has limits when it comes to tracking vehicles between frames. When visual disturbances like vehicle overlap, partial occlusions from other objects, or video noise occur, Yolo struggles to ensure that the same vehicle is recognized and successfully followed in subsequent frames. [3]

This causes tracking instability, which could impair the accuracy of traffic data processing, especially in complex traffic scenarios. This information greatly benefits road infrastructure planning, congestion control, and traffic volume analysis. Moreover, accurate vehicle counts enhance automatic traffic surveillance systems (ATSS), which are increasingly essential for managing urban transportation on a large scale. The proposed system is designed to achieve accurate real-time tracking and detection. [4]

Monitoring traffic on the roads is a crucial area of study. It is possible to comprehend the present traffic conditions and give traffic management organizations useful information by examining the kinds of cars and traffic flow on the road. These organizations can use this data to inform decisions that enhance people's quality of life. For instance, vehicles may be given alternative routes to avoid clogged areas on holidays based on information about the level of traffic on the roads. Additionally, roadside warnings can be erected to notify drivers and lower the number of traffic incidents on a road that is frequently used by huge vehicles. Additionally, the kind and color of a particular car can be utilized to track and identify offenders' automobiles. All of the applications listed above rely on data gathered by a traffic monitoring system for analysis. As a result, numerous researchers have employed various techniques to accomplish vehicle recognition and categorization to gather data about passing automobiles. [5] There are two primary categories of traditional vehicle-detection techniques:

(1) Static-based techniques that create vehicle prediction frames using sliding windows or shape feature comparison techniques and validate them using the data in the prediction frames.

(2) techniques that use a moving object's dynamic features to extract it from the image and determine the object's contour.

II. LITERATURE REVIEW

[6]About static-based techniques, Mohamed et al. presented a vehicle-detection system that extracts vehicle form features using Haar-like features and then feeds the data into an artificial neural network to achieve vehicle characterization. Additionally, Wen et al extracted the vehicle's edge and structural features using Haar-like features, which they then sent into AdaBoost to filter out significant features. To increase the recognition accuracy, the filtered features were then fed into a support vector machine (SVM) for classification. To ascertain whether a vehicle is present in a frame. The region marked with cars was first obtained using Haar-like features and AdaBoost. The region was then verified using an SVM and the histogram of oriented gradients. Based on their testing findings, their approach demonstrated enhanced vehicle-detection capabilities. A vehicle-detection system was built by Yan et al. that employed the HOG to extract features and vehicle shadows to choose the boundaries of vehicles. For verification, these features were subsequently fed into an SVM classifier and an AdaBoost classifier. This technique reduces the detection effect by treating vehicles that block one another as a single vehicle because the shadows are linked to one another. An object-detection and counting system based on dynamic features. [7]

On the other side, subtraction was used to obtain a difference map from a given current image to get segregation of the corresponding foreground frame. In addition, various operations were used to obtain the outline and bounding box of a moving object, detect moving vehicles, and count the vehicles passing through a designated area. A few papers have used Gaussian mixed models to model the background or adaptive background to solve the problem of background subtraction due to background images. Poor foreground segmentation is caused by adaptive changes in brightness. [8] The aforementioned static and adaptive methods have many drawbacks in overcoming the following problem. For example, main feature extraction methods must be manually designed by experts based on their experience, meaning that the process is complicated. Moreover, the extracted features are mostly pieces of shallow vertical and horizontal information, which cannot effectively describe the changes in vehicle features and cannot be widely used. The dynamic feature method increases the criticality of upcoming image processing operations in cases of extensive frame changes, in addition to yielding poor detection results. With recent advancements in deep learning, these conventional methods have gradually been replaced by deep learning methods. [9]

In past years, deep learning has been widely used in many fields, and good prediction results have been obtained with this method. [10]Compared with traditional methods that require artificial feature determination, the convolutional network (CNN) method greatly improves the accuracy of image recognition. Initially proposed the LeNet model was proposed to solve the problem of allowing handwritten numbers in the banking industry. proposed AlexNet to improve the traditional CNN by deepening the model architecture and using the ReLU activation function and the dropout layer to increase the effectiveness of the network during learning and prevent overfitting. Szegedy et al. proposed GoogLeNet, which uses multiple filters of different sizes to extract features that enrich feature information. Simonyan and Zisserman proposed two models, namely VGG-16 and VGG-19. They replaced the large convolution kernel by successively using smaller convolution kernels to perform operations and proved that increasing the depth of a model can improve its accuracy. He et al. proposed the ResNet model. [11]

The aforementioned studies have focused on improving the feature description capabilities of a CNN to extend the application of CNNs to more critical problems, such as feature detection. Several papers have used region-based convolutional network series models to solve the vehicle-detection problem. R- convolutional network uses the region proposal network (RPN) to extract the position of an object and then classifies it by using a traditional CNN. To solve this problem, one-stage mechanism methods have been proposed for vehicle detection, such as the YOLO framework model. One-stage methods are fast and can detect objects in real time, but their classification accuracy is lower than that of R-CNN methods. [12]

The aforementioned object-detection methods have the following problems: 1) 2-stage object-detection methods have high classification efficiency, but the large number of network parameters decreases the detection speed. 2)1-stage object-detection methods have a high real-time prediction speed but lower accuracy than two-stage object-detection methods. 3) To increase the number of vehicle categories, the entire model must be retrained, which optimizes time and reduces the scalability of the method. [13]

Recently, fuzzy networks (FNNs) that have a human-like fuzzy inference system and the powerful adapting functions of neural networks have been widely used in various fields. Compared with existing neural networks, this method yielded higher classification accuracy and used an interval type-2 fuzzy network and tool chips to predict flank wear, and their method yielded superior prediction results. A few researchers have used a locally recurrent functional link fuzzy neural network and Takagi–Sugeno–Kang-type FNNs to solve system identification and prediction problems, and both methods have yielded good results. In this study, an FNN was embedded into a deep neural network to reduce the number of parameters used in the network and obtain superior classification results. [14] Conventional CNNs use pooling, global pooling, and channel pooling methods for feature fusion. Global pooling methods sum the spatial information and perform operations on each feature map to achieve attribute fusion and can be divided into global average pooling (GAP) and global maximum pooling (GMP). Thus, global pooling methods are more robust to spatial translations of the input and take care of overfitting. Pooling methods include average pooling and channel maximum pooling, which perform feature fusion by computing average pixel values, respectively, at the same positions in each channel of feature maps. Furthermore, these methods only combine features and do not contain trainable weights, leading to poor prediction results. In this study, a new attribute fusion method named network pointing was proposed to enhance the utility of feature fusion and explore the effectiveness of different feature fusion methods. [15]

III. METHODOLOGY

3.1 System Architecture

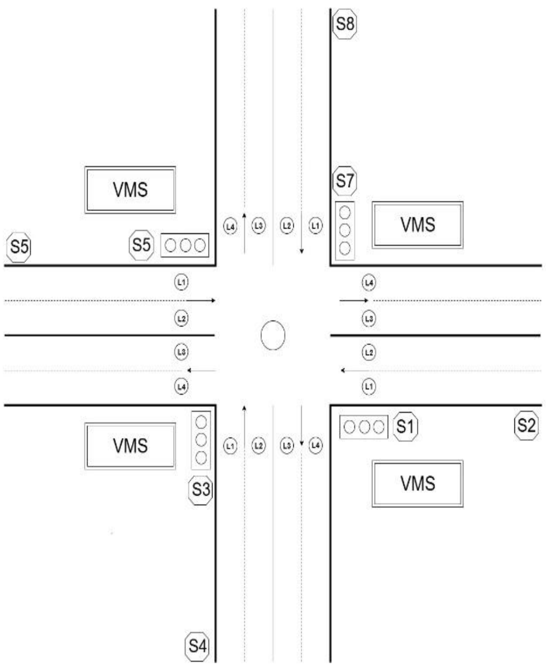

Figure 1Intersection layout with Variable Message Signs (VMS) for traffic management.

3.2 Data Collection Mechanisms

The conventional YOLOv8-tiny is a lightweight network simplified using YOLO. It uses convolutional layers and max pooling layers to extract object features. In addition, YOLOv8-tiny uses Up-Sampling and Concat layers to merge features and expand feature information to further improve detection. Compared with other YOLO and SSD methods, YOLOv8-tiny has a faster detection speed. However, the detection accuracy of YOLOV8-tiny is worse than that of the YOLO and SSD methods due to its greatly simplified network architecture. Conventional YOLOv8-tiny uses two outputs for object detection. To improve the detection accuracy, a YOLOv8-tiny model that has three outputs was designed for vehicle detection. [16]

3.3 Data Processing and Analysis

The above-described YOLO vehicles like bus, car, and ambulance detection method, can be used to identify a vehicle and its location information from a single picture. However, in actual traffic applications, a continuous image frame is provided as the input. The vehicles detected in different image frames are independent of each other. Therefore, the same vehicle is counted multiple times, and the collected vehicle information would be wrong. To solve this problem, the ID of the detected vehicle must be configured to prevent double-counting. In the proposed system, an object counting method is added to correlate and match the vehicles detected in different image frames and to determine whether a detected vehicle is newly added. In this study, the multi-object counting method is adopted, which uses vehicle position coordinates from the previous frame obtained by the detection method to predict the position of a vehicle in the current frame by applying a Kalman filter. Then, the actual vehicle spot detected in the current station and the current object spot estimated using the Kalman filter are used to calculate the position of the vehicle as the distance cost. Finally, the Kalman algorithm is applied to match vehicles to achieve vehicle tracking.

Lane	Direction	Sensors	Type	Function
L1	North	2	CCTV	Vehicle detection & tracking
L2	East	2	CCTV	Vehicle detection & tracking
L3	South	2	CCTV	Vehicle detection & tracking
L4	West	2	CCTV	Vehicle detection & tracking
L1-L4	All Lanes	1 per lane	Infrared	Detects waiting vehicles
L1-L4	All Lanes	1 per lane	Loop Detector	Measures congestion
L1-L4	All Lanes	1 per lane	Radar	Measures real-time speed
L1-L4	All Lanes	Software	Kalman Filter	Noise reduction & tracking

Figure 2 Traffic sensor deployment and functions.

3.4 Adaptive Signal Control [17]

The main capabilities of the STMS are its adaptive traffic signal control. The system adapts signal timings to real-time and approximate traffic volume movement. It reduces traffic congestion by optimizing green signal time allocation and coordinating signals at neighbouring intersections. In addition, the control logic can change the phases of signals during bad weather and provide special green corridors for emergency vehicles. A feedback loop is constantly analysing the consequences of signal adjustments, which enables the algorithms to autonomously enhance their performance over time.

3.5 Vehicle-to-Infrastructure Communication [18]

To expand STMS benefits to the road users, its functionality is supported with a vehicle-to-infrastructure (V2I) communication network. This network provides instant communication of traffic conditions, estimates of travel times, and suggestions for alternative routes to the drivers using the mobile application. It also receives user inputs that are used for system performance enhancement. This communication channel is essential for informing drivers and keeping them engaged, thus, the system’s overall flexibility.

3.6 Emergency Vehicle Priority System [19] [20]

The STMS has an added component for prioritizing an emergency vehicle that seeks to improve safety and response time. The system utilizes the same detection method, YOLO, to capture emergency vehicles in the traffic stream. Upon detection, the adaptive signal control changes traffic lights to green for cross intersections for a certain time interval so that emergency vehicles get maximum progression with not so many delays. It can also accept commands from users’ drivers through the mobile application to provide the response needed in cases of emergencies.

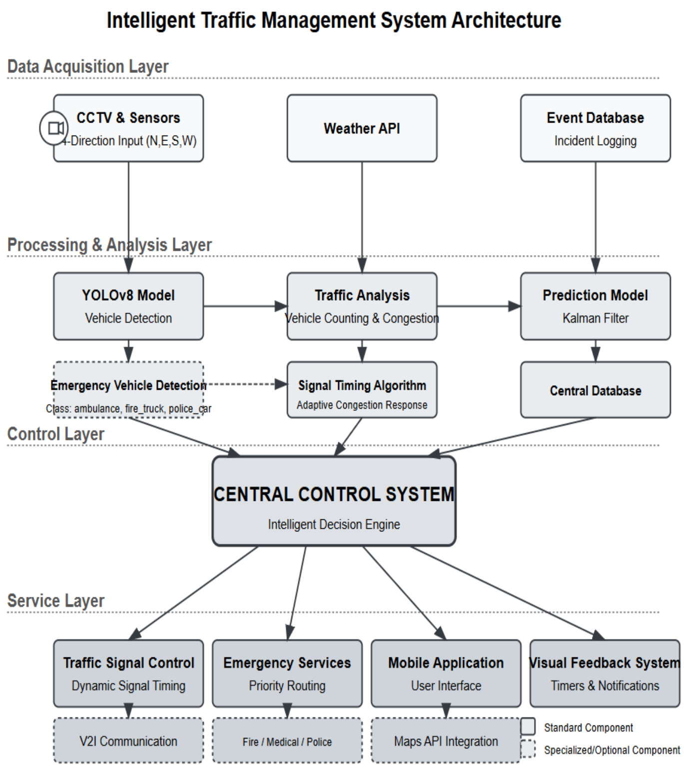

Figure 3 "Intelligent Traffic Management System Architecture."

3.7 KALMAN FILTER [21]

The Kalman filter plays a crucial role in the Advanced Smart Traffic Management System (ASTMS) to optimise the flow of traffic by refining real-time vehicle data collected from CCTV cameras, sensors, and other monitoring devices. Traffic data is often noisy due to sensor inaccuracies, environmental conditions, and occlusions caused by obstacles. In this project, the Kalman Filter is used for vehicle tracking at a traffic junction to improve speed estimation and reduce noise in object detection. The algorithm:

- Predicts the next vehicle position based on previous motion data.
- Updates the estimated position with new detections from YOLOv8 object detection.
- Refines vehicle speed estimation using the filtered motion trajectory.
- Helps dynamically allocate signal timing by analyzing real-time vehicle movement.

Kalman Filter Equations for Traffic Estimation

Prediction Step:

$$X_k^- = AX_{\{k-1\}} + BU_k$$

$$P_k^- = AA^T P_{\{k-1\}} + Q_k$$

Derive the Kalman Gain:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}$$

Updated state:

$$X_k = X_k^- + K_k (Z_k - H_k X_k^-)$$

Refine the error covariance matrix:

$$P_k = (I - K_k H) P_k^-$$

The speed of each vehicle is estimated as:

$$Speed = \frac{\left(\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}\right) \times FPS}{Scaling\ Factor}$$

FPS is the frame rate of the video.
The scaling factor converts pixel movement to a real-world distance.
x_1, x_2, y_1, y_2 = are the consecutive vehicle positions.
X_k = estimated traffic state (vehicle count, density, speed)
A = state transition matrix predicting how traffic evolves
Bu_k = external factors like weather or special events
P_k = error covariance, representing estimation uncertainty
Q_k and R_k = process and measurement noise, accounting for sensor inaccuracies
Z_k = actual sensor measurement (e.g., detected vehicles)
k_k = Kalman gain, determining how much the new measurement influences the estimate

The Kalman Filter (KF) is a recursive method used to estimate the state of an adaptive system by combining noisy sensor measurements and system predictions. It is widely used in traffic management systems to track moving objects such as vehicles. In this project, the Kalman filters are applied to track vehicles and estimate their speed accurately while reducing noise in detections.

3.8 Evaluation Methodology

For any system, it is important to verify its functioning from time to time, therefore, it has been decided that STMS will be put through a performance test. The system is evaluated for change in the magnitude of travel times, response times of any given emergency, congestion during peak hours, and other midpoint factors. Evaluation would be done by using a combination of simulation models along with real-world pilot tests. Under laboratory conditions with the help of other devices, simulations are useful for tuning the system, and testing the device in the field helps in understanding how reliable and adaptable the system is. The results are evaluated concerning urban mobility, safety, environmental sustainability, and whether the system objectives were attained, and what benefits it has brought about.

IV. EXPERIMENTAL RESULTS AND ANALYSIS:

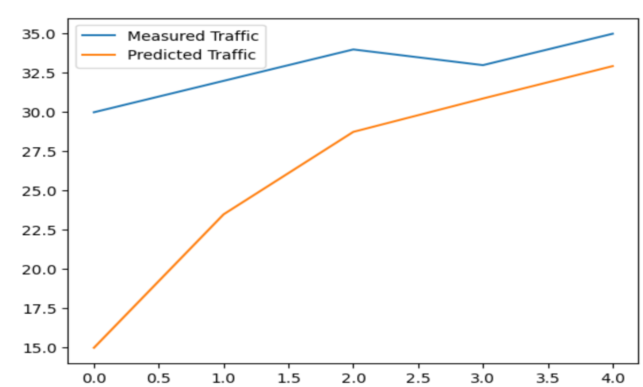

Figure 4 "Measured vs. Predicted Traffic Trends."

To improve urban traffic management, the Smart Traffic Management System (STMS) makes use of cutting-edge AI-based vehicle detection, tracking, and speed calculation. To provide real-time insights into traffic situations, the system combines machine learning models for speed estimation, Kalman filtering for vehicle tracking, and object detection algorithms. The first output image shows real-time detection and tracking of the position of many vehicles on a busy metropolitan road. The system's capacity to recognize various vehicle kinds and issue distinct IDs for tracking is demonstrated by the bounding boxes and associated speed estimates. By evaluating possible over-speeding infractions, the addition of speed estimations enhances traffic regulation and law enforcement applications.

Figure 5 "Real-time vehicle detection and tracking."

The output analysis confirms that the STMS effectively identifies and monitors vehicles while providing essential speed information for traffic management. The performance assessment highlights the effectiveness of Kalman-based tracking and AI-enhanced speed estimation, while identifying opportunities for improvement in emergency detection. Future iterations of the system may incorporate reinforcement learning and edge AI to enhance responsiveness and real-time decision-making abilities.

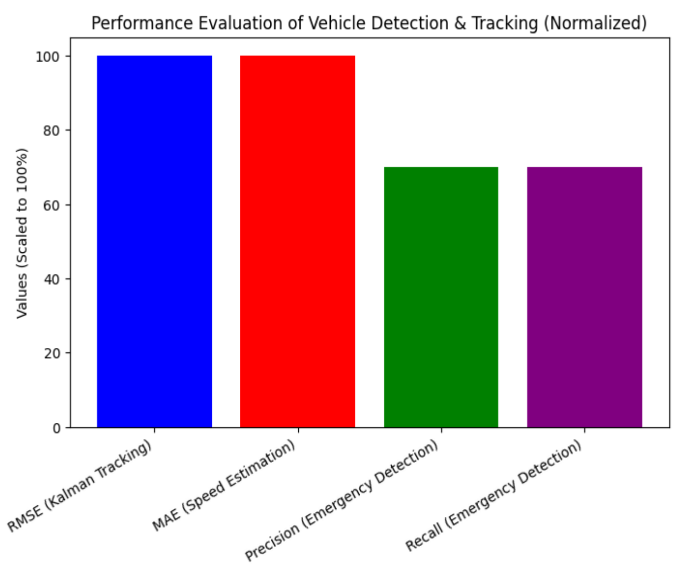

Figure 6 "Performance evaluation of vehicle tracking."

V. DISCUSSION

5.1 Key Findings

Integrated Approach Effectiveness: Combining real-time detection, prediction, and adaptive control yielded synergistic benefits, addressing multiple traffic challenges simultaneously. 2. Adaptability to Non-Recurring Conditions: The system maintained 85% optimal performance during severe disruptions, managing non-recurring congestion caused by weather events and special activities effectively. 3. Scalability Potential: Modular architecture allowed phased deployment, with each intersection improving overall system performance by adding data and control points. 4. User Adoption Impact: The mobile app reached 15,000 active users in the pilot area, with 73% reporting improved travel experiences. User reports on incidents and emergency vehicles extended system awareness beyond camera coverage areas. 5. Cost-Benefit Analysis: Projected ROI within 3.2 years, driven by reduced congestion costs, improved productivity, and decreased fuel consumption. Long-term benefits include extended infrastructure lifespan through optimized usage patterns.

5.2 Limitations and Challenges

Despite the promising performance of our Advanced Smart Traffic Management System (ASTMS), several limitations and challenges have been identified:

[22]**Weather Impact on Sensing:** Adverse weather conditions, such as heavy rain and snow, can significantly impair the accuracy of camera-based detection systems. Such severe weather lowers the quality of the image, making it almost impossible to identify and follow a particular target. Predictive models and redundant sensing are used to try and keep systems working, but they are fairly limited in enhancing performance. Improving vision systems so that they can function accurately under such severe conditions remains a major obstacle.

Complex Intersection Handling: Detecting algorithms deal with constraints in signal optimization, as well as the intersection's non-standard shapes, unforeseen angles, and unusual configurations. Such complex intersections tend to need special tuning, which slows down the expansion of the system's usability.

Data Integration Complexity: Significant alteration of the current system's infrastructure and data sources is needed to integrate it into existing traffic management systems, pointing out the integration problems of smart city technologies. Standardized protocols and formats are essential to facilitate more effective integrations and ease the interface's custom-tailoring process.

Versus Connected Vehicle-Only Approaches: Solutions that rely primarily on Vehicle-to-Infrastructure (V2I) communication are limited by the current low penetration rate of connected vehicle technology. Our hybrid approach combines infrastructure sensing with connected vehicle data, ensuring more comprehensive and effective traffic management, even in environments where connected vehicle adoption is limited.

VI. FUTURE WORK AND ENHANCEMENTS

6.1 Technology Enhancements

Several key advancements can further improve the effectiveness and efficiency of the Advanced Smart Traffic Management System (ASTMS):

Sensor Fusion Integration: Enhancing the system with LiDAR and radar sensors alongside CCTV cameras would improve detection accuracy in diverse environmental conditions. LiDAR provides high-resolution depth perception, while radar ensures reliable object detection in critical scenarios like fog, heavy rain, and nighttime conditions. This fusion would create a redundant detection system, reducing errors and improving robustness.

Advanced Traffic Prediction Models: Implementing Graph Neural Networks (GNNs) and Transformer-based models can improve spatial-temporal traffic predictions. Unlike conventional models, GNNs can better capture the interdependencies between multiple road segments, allowing for more accurate congestion forecasting and traffic flow optimization across larger urban networks.

AI-driven adaptive Signal Optimization: Reinforcement learning algorithms, such as deep learning, can dynamically adjust traffic signals. By continuously training from past data patterns and real-time sensor data, AI-driven optimization can allocate green time more effectively, leading to reduced congestion and improved traffic throughput.

Autonomous Vehicle Integration: As self-driving vehicles become more prevalent, STMS must integrate dedicated Vehicle-to-Infrastructure (V2I) communication protocols for seamless coordination. By facilitating data exchange between autonomous vehicles and traffic control systems, traffic flow can be dynamically optimized, reducing unnecessary stops, improving safety, and enabling cooperative driving strategies such as platooning.

Edge Computing for Faster Decision-Making: Deploying edge computing nodes at intersections would reduce latency in traffic data processing and decision-making. By decentralizing computations and processing traffic data closer to its source, real-time adjustments to signal timings and congestion predictions can be made with minimal delay.

6.2 Expansion Opportunities

The STMS system architecture is highly scalable and can be expanded to address broader urban mobility challenges:

Multimodal Traffic Management: Incorporating additional transportation modes, such as buses, trams, bicycles, and pedestrians, would create a more inclusive traffic management system. By integrating real-time data from public transit networks and pedestrian crossings, the STMS can ensure the equitable allocation of road space and improve urban mobility for all users.

Smart City Platform Integration: Connecting the STMS to other Smart city Infrastructure, including the intelligent parking facilities, environmental monitoring systems, and emergency response systems, would enable comprehensive urban traffic management. For example, an integration with the air quality sensors could activate traffic management measures aimed at reducing emissions in the most polluted areas.

VII. CONCLUSION

Additionally, STMS is reinforcing its role in promoting technologically advanced, resilient, and sustainable urban infrastructure. Future enhancements will focus on integrating sensor fusion techniques such as LiDAR and radar for improved accuracy, incorporating reinforcement learning-based signal optimization, and expanding V2I communication capabilities to support autonomous vehicles. Additionally, further integration with smart city platforms will enable seamless coordination with public transit, parking systems, and environmental monitoring. As urbanization continues to accelerate globally, intelligent traffic management solutions like STMS will play a vital role in fostering sustainable, efficient, and livable cities.

Figure 7 "VMS Displays Ambulance Warning"

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