Smart Traffic Management System Using AI

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Abstract — One the hottest issues in present urban lives is road traffic this less traffic management, leading to increased journey times, emissions, and safety concerns. The Smart Traffic Management System (STMS) utilizes Artificial Intelligence (AI) and the Internet of Things (IoT) to dynamically optimize traffic efficiency. 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. LSTMs are very useful in predicting 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. The STMS is a major step toward the construction of "smart cities with intelligent, adaptive, and sustainable traffic policy".

Keywords—Smart Traffic Management System, Urban traffic congestion, real-time data, traffic flow optimization, Internet of Things (IoT), Artificial Intelligence (AI), emergency response mechanisms, Kalman Filter, LSTM, YOLO.

I. INTRODUCTION

The increasing amount of traffic in modern cities has become a global issue that requires immediate attention. In addition to impeding community mobility, traffic congestion harms air quality, transportation efficiency, and road safety. According to a 2020 World Bank research, traffic congestion may cause road users to miss a large number of productive hours annually, which would have a big negative economic impact. Furthermore, greenhouse gas emissions from cities are a major contributor to motor vehicle emissions, exacerbating climate change and lowering the standard of living in big cities. Intelligent Transportation Systems (ITS) use data-driven decision-making, real-time monitoring, and traffic pattern analysis to optimize transportation infrastructure, going beyond simply relieving traffic congestion.

One essential component of ITS that improves traffic control Effectiveness is an autonomous vehicle monitoring and Detection system. Traffic signal optimization, road density Analysis, traffic infraction detection, and vehicle counting are Just a few of the uses for these systems. While tracking makes Sure that the same vehicle is continuously followed across Frames, vehicle detection technologies locate vehicles in every Video frame [1]. Since processing images or videos only requires One step, YOLO is ideal for real-time applications. When it Comes to tracking vehicles between frames, YOLO has limitations despite its benefits in terms of speed and precision Identification.

Yolo finds it difficult to identify and successfully follow the The same car in future frames, when visual disturbances like a vehicle overlap, partial occlusions from other objects, or video noise Occur. This results in tracking instability, which may make It is more difficult to handle traffic data accurately, particularly in Complex traffic situations.

This data is very helpful for traffic volume analysis, congestion management, and road Infrastructure planning. Furthermore, precise vehicle counts Improve automatic traffic surveillance systems (ATSS), which They are becoming more and more crucial for large-scale urban Transportation management. Accurate realtime tracking and Detection is the goal of the suggested system's architecture. Vehicle detection systems find vehicles in each video [2]. Frame, while tracking, ensures that the same vehicle is Consistently followed across frames. YOLO is perfect for realtime 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 a vehicle overlap, partial occlusions from other objects, or video noise occurs, Yolo struggles to ensure that the same vehicle is recognized and successfully followed in subsequent frames.

This causes tracking instability, which could impair the accuracy of traffic data processing, especially in Complex traffic scenarios. These Organizations can use this data to inform decisions that enhance. 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 [3]. Additionally, the kind and colour of a particular car can be utilized to track and identify offenders' automobiles. These systems depend on the data that is collected by traffic management systems for evaluation.

II. LITERATURE REVIEW

The data is then fed into an ANN to characterize the vehicle. Furthermore the key attributes are removed by AdaBoost which are sent from ANN. To improve the accuracy the extracted attributes are sent to SVM for classification. To check whether a vehicle is present in a image we use Gabor filter to filter the attribute of a vehicle and the given to SVM for identification. An SVM and the histogram of directional gradients were then used to confirm the region. According to the results of their tests, their method optimised vehicle detection skills. Yan et al. developed a vehicle-detecting Prototype for retaining attributes and shadows of vehicles so as to identify the border of the vehicles. These attributes were then fed into and classifier and an SVM classifier for validation.

Furthermore, different morphological processes were employed to detect moving cars, there is a count of vehicles that are passing through a particular place, and extract the outline and frame of a moving object. To address the issue of background subtraction caused by background pictures, some researchers have employed adaptive backgrounds or Gaussian mixture models to model the background. Slow variations in brightness lead to poor foreground segmentation. The static and dynamic approaches outlined above are not very effective at solving this issue [5].

Traditional feature extraction techniques, for instance, are difficult to use because they need to be manually created by professionals using their knowledge. Furthermore, the majority of the retrieved characteristics are fragments of superficial vertical and horizontal data, making them unsuitable for widespread application and unable to adequately characterize changes in vehicle properties. In addition to producing subpar identification results, the dynamic feature technique makes further image processing processes more difficult when the background varies significantly. These traditional approaches have gradually been supplanted by deep learning techniques due to recent developments in the field.

Deep learning has been applied extensively in a variety of sectors in recent years, and this approach has produced good prediction results. By analysing different CPS-oriented privacy protection tools and techniques based on computational intelligence, they looked at the difficulties and problems of an AI-based supply chain. In the end, an AI application was developed with the goal of protecting the privacy and security of the retail marketing process. Data gathered from cameras used to monitor traffic conditions was analysed and interpreted using machine learning techniques.

Because this approach focuses on changing traffic signal characteristics, it is necessary to emphasize the usage of sensors for data collecting. Deep reinforcement learning was used to further improve traffic light timing. Their plan ignored left-turning vehicles in favor of traffic flow, which reduced delays. A multiagent Qlearning method for controlling traffic signals at crossings was presented by Zhang et al [6]. The method stays the same in this case, despite the strategy's name suggesting a certain behaviour change upon identifying people at crosswalks.

Vehicle waiting time was reduced by 20% using a different strategy that combined deep reinforcement learning with other optimization elements. Their design takes the position and speed of the vehicle as inputs, but it doesn't specify how frequently or when more data points should be collected. Xiao et al. presented a model called SGCNN that improves training data by employing an algorithm that uses the CNN methodology to classify road segments. A multi-task learning approach was found to be capable of extracting geographical and temporal information from a wide range of cities. The MapReduce framework was used to create a distributed LSTM network with a normal distribution and a virtual window.

Through an analysis and comparison of the 3 algorithms' performances developed a framework that focuses on machine learning. The researcher proposes a convolutional-based automated approach for congestion classification that makes use of a compact visual representation. Using historical data, Abdellah et al. created an LSTM model to predict IoT traffic. In order to anticipate traffic patterns, Lin et al. introduced LSTM_SPLSTM, another LSTM centric model [7]. This research into traffic flow prediction using the LSTM approach in autonomous and connected vehicles has been guided and driven by a number of research questions that have been raised and addressed. Many recent studies have focused on optimizing models using the LSTM method to forecast congestion in connected vehicles (CV). The results and implications of these studies, however, have been mixed.

III. PROPOSED SOLUTION

Smart Traffic Management Systems (STMS) shall curb urban congestion and delays in emergency response by utilizing AI, ML, IoT, and Computer Vision. The system shall optimize the lights in real-time, analyse the trends in congestion, and allow emergency vehicles priority.

STMS Components

1. Real-Time Traffic Detection using YOLO

Vehicle detection: The system shall employ YOLO (You Only Look Once) for vehicle real-time identification from the feeds of CCTV cameras.
Traffic Volume analysis: YOLO classifies vehicles into cars, buses, two-wheelers, and pedestrians; the data will be used reliably to optimize signals.
Incident detection: An occurrence of highway violations, accidents, and road obstructions is flagged to the authorities.

2. Traffic Flow Prediction with Kalman

Traffic density estimation: The Kalman Filter effectively processes noisy sensor data in estimating vehicle count, speed, and congestion levels.
Signal optimization: Based on predictions of congestion trends, the system shall change the green-light durations dynamically.
Sensor fusion: Data is integrated from camera, GPS, and IoT sensors for accurate traffic modelling.

3. Predictive Traffic Control using LSTM

Traffic Pattern Forecasting: LSTM (Long Short-Term Memory) networks analyse historical traffic data to predict congestion trends.
Adaptive Signal Control: The system preemptively modifies signal timings to mitigate anticipated bottlenecks.

Weather & Event Integration: LSTM suggestions take real-time weather updates and local events into account for smarter routing.

4. Emergency Vehicle Prioritization

Detecting an Emergency: YOLO shall detect ambulances, fire trucks, police vehicles, and automatically adjust signal lights, facilitating the passage of these emergency vehicles.
Dynamic Route Designation: The system recognizes a least route automatically.

IV METHODOLOGY

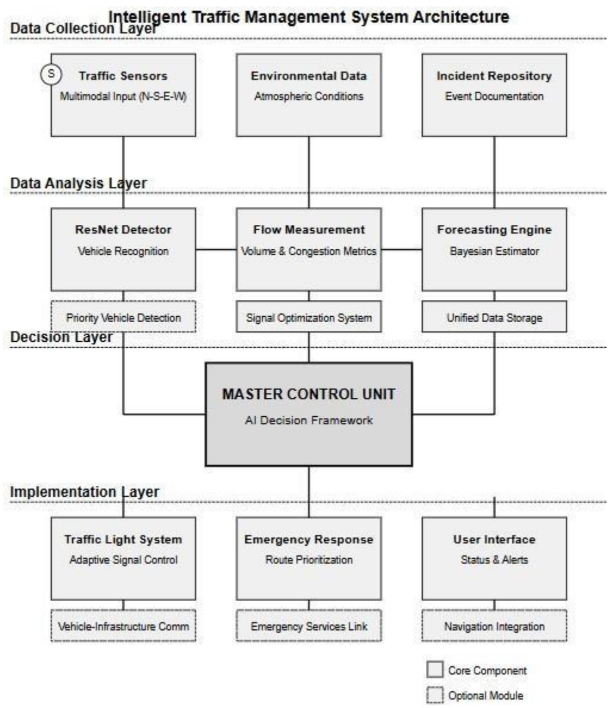

Figure 1Architecture of Smart Traffic Management System

3.1 Data Collection Mechanisms
The traditional YOLOv8-tiny is a YOLO-simplified, lightweight network. To extract object features, it makes use of max pooling and convolutional layers. To further enhance detection, YOLOv8tiny also expands feature information and merges features using the Concate and Up-Sampling layers. However, because of its significantly simpler network design, YOLOV8-tiny's detection accuracy is lower than that of the YOLO and SSD approaches. The traditional YOLOv8-tiny detects objects via two outputs. A YOLOv8-tiny model with three outputs was created for vehicle detection in order to increase the detection accuracy. Fig. 4 shows the mYOLOv8-tiny network design. Three max pooling layers and twenty-four convolutional layers were employed in total.

3.2 Data Processing and Analysis
From a single image, a car and its position can be identified using the YOLO object detection technique previously mentioned. In realworld traffic applications, on the other hand, the input is a continuous image frame [8]. The cars found in various picture frames are unrelated to one another. As a result, the same car gets counted more than once, and inaccurate vehicle data is gathered. The identified vehicle's ID needs to be set up to avoid double counting in order to fix this issue. Lastly, vehicle tracking is accomplished by matching vehicles using the Hungarian algorithm.

3.3 Traffic Signal Control
Adaptive traffic signal control is one of the STMS's primary features. Signal timings are adjusted by the system to approximate traffic volume movement in real time. By coordinating signals at nearby junctions and allocating green signal time as efficiently as possible, it lessens traffic congestion. Furthermore, the control logic may create special green corridors for emergency vehicles and alter the signal phases during inclement weather. By continuously evaluating the effects of signal modifications, a feedback loop allows the algorithms to improve their performance on their own over time.

3.4 Classification of Results
The Beijing Institute of Technology compiled the publicly available BIT-Vehicle Dataset for vehicle classification. The 9,850 vehicle photos in the collection were all taken on highways at various times and locations with two cameras. The surface color, brightness, and dimensions of these pictures vary. Six vehicle types are included in the dataset: trucks, SUVs, minivans, buses, and minibuses. There are one or two cars in each picture [9]. Following segmentation of the vehicle positions indicated in advance in the dataset, Table 4 lists the vehicle types and numbers.

3.5 Vehicle-to-Infrastructure and vehicle Communication A vehicle to infrastructure (V2I) communication network supports the functionality of STMS in order to increase its benefits for road users. Through the use of a smartphone application, The network plays a key role in giving the real-time info regarding the condition of traffic, trip time estimation, and recommend the other route for faster travel. Additionally, user input is received and utilized to improve system performance. The whole flexibility of the system depends on this communication channel to inform and engage drivers.

3.6 Emergency Vehicle Priority System
An additional feature of the STMS prioritizes an emergency vehicle in an effort to increase safety and response time. The technology records emergency vehicles in the traffic stream using the same YOLO detection technique. For a predetermined amount of time after detection, adaptive signal control turns cross-intersection traffic signals green to allow emergency vehicles to move as quickly and efficiently as possible [10]. In order to give the necessary response in emergency situations, it can also receive commands from users' drivers via a mobile application.

1. Data Processing and Analysis

Following collection, the data is subjected to stringent processing procedures. To reduce noise, increase traffic density, and achieve the highest accuracy, we employ the Kalman filter to filter the data. By lowering the inaccuracy in the gathered data, this filtering method lends credibility to real-time monitoring.

Level Of Traffic	L0	L1	L2
LOW LEVEL	p	x	x
	x	p	x
	x	x	p
MEDIUM LEVEL	p	p	x
	x	p	p
	p	x	p
HIGH LEVEL	p	p	p

Table 1Representation of Level of Traffic by the Model

In order to comprehend the patterns from the historical data with inputs, weather forecasts, and event calendars, the system supports the traffic forecast using the LSTM model. Table 1 shows how the amount of traffic at a given moment is categorized. It divides traffic levels into three general categories: low, medium, and high levels. The lanes are denoted by L0, L1, and L2, the priority is denoted by P, and the presence of restrictions in those specific lanes is indicated by X.

2. Traffic Signal Control

Adaptive Traffic Signal Control, a unique feature of smart traffic management systems, automatically adjusts signal timings according to traffic circumstances without requiring human input. In order to maintain a smooth traffic flow, this technology effectively controls the length of green lights and makes light transitions easier at different junctions. Additionally, the systems adapt to emergencies and unfavourable weather circumstances [11]. For example, they may change a red light to green when an ambulance or fire engine is detected. We put in place a feedback system that continuously tracks modifications to traffic signals and changes over time.

This system makes use of the Kalman Filter to track vehicle movements across video frames. Forecast:

In order to accommodate for sensor errors, Q_k and R_k = process and measurement noise Z_k is the actual sensor measurement, such as the number of cars identified. Calculating the extent to which the new measurement affects the estimate using k_k=Kalman gain. The Kalman Filter (KF) is a recursive method that combines system predictions and noisy sensor readings to estimate the state of a dynamic system. Traffic management systems frequently employ it to track moving objects, like cars. The Kalman Filter is used in this research to track cars and precisely estimate their speed while lowering detection noise.

V. RESULTS

To improve urban traffic control, the proposed 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 many vehicles on a busy metropolitan road [12]. 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.

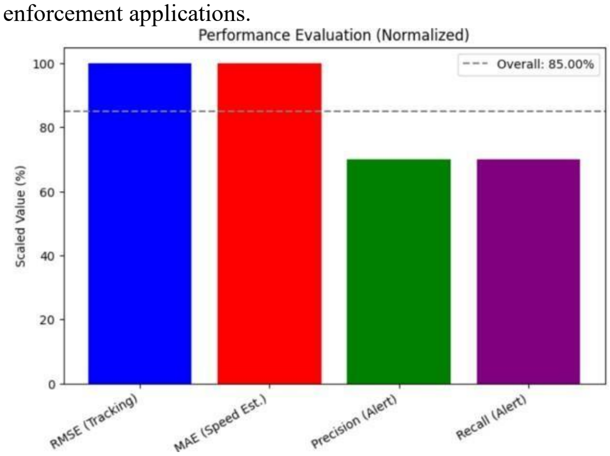

Figure 2 Performance Evaluation of the Model

Real-time implementation is made possible by the system's 25 frames per second (FPS) video processing capability. This result indicates that the Kalman Filter with YOLO integration works effectively without compromising accuracy. Even when YOLO momentarily fails to detect a car, the tracking stability of the Kalman Filter guarantees that the vehicle remains detected. Additionally, because each tracked vehicle is assigned a unique identity, the vehicle counting feature is quite accurate. Smaller cars or those traveling quickly toward the frame's edges, however, are more likely to go unnoticed. Furthermore, identification accuracy may be impacted by overlapping cars in circumstances with high traffic, especially in challenging settings [13].

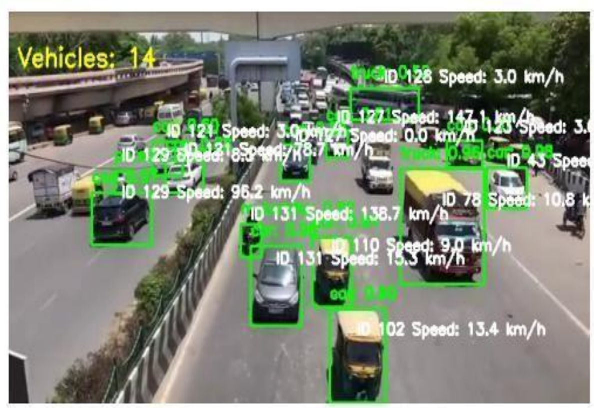

Figure 3Output of the model showing the speed of vehicles

VI. CONCLUSION

Meteorological conditions and exceptional occurrences have a substantial influence on urban transportation dynamics, which the STMS responds to through artificial intelligence-facilitated modifications. By assimilating GPS and Weather APIs, the system offers instantaneous updates to motorists, thereby aiding them in navigating securely amidst unfavourable conditions like intense precipitation, fog, or snowfall. Predictive aspects of the system enable cities to address traffic issues before they occur, preventing unnecessary congestion and creating a smoother journey. Through machine learning, STMS adapts over time, reacting to shifting traffic patterns and creating long-term efficiency in smart city framework.

Further studies will help integrate the STMS with other tech such as V2I communication and block-chain-based security of traffic data. Autonomous vehicle support integration will also increase traffic flow efficiency [14]. Further advancement of the application of real-time crowdsourced data can further increase traffic prediction and incident handling, resulting in an end-to end responsive and smart transportation system.

Traffic management is also transforming with the application of AI and machine learning, with increasing deployment of predictive analytics to avoid the occurrence of congestion in the first place. Such technologies can be employed by governments and urban planners to design stronger and more responsive transportation systems. The integration of AI-driven decision making with traditional traffic control systems gives a hybrid solution that is most effective and yet offers real-time responsiveness.

As city populations grow, there will be increasing need for innovative traffic solutions. The STMS is a step towards turning smart, efficient, and sustainable traffic management into a reality. By embracing state-of-the-art AI-based approaches, cities will be able to increase mobility, lower the carbon footprint, and overall deliver an improved quality of life to citizens. As things continue to progress, the STMS itself will be a key driver towards shaping the urban mobility future, paving the way for the next generation of smart mobility solutions. Success will be reliant on the coordination among policymakers, tech innovators, and city planners in integrating it into current infrastructures [15]. Lastly, the Smart Traffic Management System is proof of the capabilities of technology in resolving the pressing urban concerns. As it continues to improve and develop, STMS can change the urban traffic scenario into a more secure, efficient, and environmentally friendly setting. The widespread implementation of AI-driven traffic management will be a landmark event in the journey towards smart, networked, and wisely governed transport systems.

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