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ADAPTIVE TRAFFIC MONITORING: INTEGRATING ML AND VISION FOR SMART CITY TRAFFIC CONTROL

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ABSTRACT

The Vehicle Speed and Number Plate Detection System is designed to monitor vehicle speed and automatically identify vehicles that exceed speed limits, enabling the issuance of fines to offenders. The system uses a YOLOv8 pre-trained model (YOLOv8n) to detect vehicles from videos or images, and the Sort algorithm to track each detected vehicle as it moves across the camera's field of view. The vehicle's speed is calculated using the formula (V = D/T \), where the time (T) is measured as the vehicle crosses two parallel lines, and the distance (D) between the lines is computed using the Euclidean distance formula. When a vehicle is found to be speeding, the system employs a license plate detector to capture the vehicle's registration number, which is used to identify the owner for issuing a fine or "challan." The code for this project is implemented in the speed_detection.ipynb file, and test video data is stored in the video folder.

Keywords: Yolov8, Vehicle Speed Detection, License Plate Detection, Sort Algorithm, Euclidean Distance, Traffic Monitoring, Automated Fine System.

I. INTRODUCTION

The Vehicle Speed and Number Plate Detection System is an advanced AI-driven solution developed to address the growing need for efficient traffic management and law enforcement. With the increase in traffic violations, particularly over-speeding, it has become essential to deploy systems that can monitor vehicle speeds in real-time and automate the process of identifying offenders. Traditional methods of speed enforcement rely on manual monitoring or radar guns, which are not only labor-intensive but also prone to inaccuracies. This system leverages modern machine learning models and computer vision techniques to provide a more reliable and scalable approach to traffic monitoring. By integrating speed detection with automatic license plate recognition, the system is capable of seamlessly identifying vehicles that exceed speed limits and generating fines for their owners.

At the heart of this system is the YOLOv8 model (YOLOv8n), a state-of-the-art object detection algorithm that is pre-trained to recognize vehicles in video or image streams. YOLOv8 is well-suited for this task due to its high speed and accuracy, allowing it to detect and localize vehicles in real-time, even in busy or fast-moving environments. Once a vehicle is detected, the system employs the Sort algorithm to track the vehicle as it moves across the camera's field of view. This tracking is crucial because it ensures that the same vehicle is consistently identified as it crosses multiple reference points, which is necessary for accurate speed calculation.

The speed of each vehicle is calculated using a simple but effective formula: (V = D/T), where (V) represents the vehicle's speed, (D) is the distance between two parallel lines on the road, and (T) is the time it takes for the vehicle to travel between these lines. The Euclidean distance formula is used to measure (D), ensuring precise spatial calculations. By monitoring the time a vehicle takes to cross these fixed points, the system can accurately determine its speed. If the calculated speed exceeds the set limit, the vehicle is flagged as over-speeding, triggering the next phase of the process.

Once a vehicle is flagged for over-speeding, the system activates a license plate detection mechanism, which captures the registration number of the offending vehicle. This information is then used to identify the vehicle owner and automatically generate a fine or "challan" for the violation. The use of automated license plate recognition (ALPR) eliminates the need for human intervention, streamlining the process of traffic law

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enforcement and significantly reducing the time and resources required to handle over-5speeding cases. The integration of vehicle detection, speed tracking, and license plate recognition makes this system a comprehensive solution for modern traffic management.

II. LITERATURE REVIEW

The development of intelligent traffic monitoring systems has gained significant attention in recent years due to the need for more efficient and accurate traffic law enforcement. Traditional methods for speed detection, such as radar guns and speed cameras, have limitations in terms of accuracy, scalability, and human resource dependency. As a result, researchers and developers have turned to machine learning and computer vision technologies to create automated systems capable of real-time monitoring. Object detection algorithms, such as YOLO (You Only Look Once), have been widely adopted due to their ability to perform fast and accurate detection of multiple objects in dynamic environments. The evolution from earlier versions like YOLOv3 to YOLOv8 has further improved detection accuracy, making it a preferred choice for vehicle detection in traffic systems.

The application of the YOLO model in traffic management has demonstrated notable success, particularly in vehicle detection tasks. YOLOv8, the latest iteration of the YOLO series, offers enhanced real-time performance and precision in detecting vehicles from video streams, even in challenging conditions such as varying lighting, weather, or heavy traffic. Studies show that YOLO's performance in object detection is highly efficient due to its capability to detect multiple objects within a single frame. This model's speed, accuracy, and ability to work with relatively low computational resources make it ideal for use in systems like vehicle speed detection, where high frame rates and immediate decision-making are crucial.

In conjunction with YOLO, the Sort (Simple Online and Realtime Tracking) algorithm is commonly employed in traffic monitoring systems for tracking objects over time. Sort is a tracking-by-detection algorithm that excels in maintaining the identity of detected objects as they move through the camera's field of view. It uses Kalman filtering and the Hungarian algorithm to associate new detections with existing tracks, ensuring consistent vehicle tracking. This capability is particularly useful for calculating speed, as it enables accurate time measurements between the vehicle's entry and exit across predefined lines. The combination of YOLO for detection and Sort for tracking creates a robust framework for monitoring vehicles in real-time.

For identifying traffic violators, automatic license plate recognition (ALPR) systems have been integrated into speed detection frameworks. ALPR technology has matured significantly over time, benefiting from advances in optical character recognition (OCR) and deep learning techniques. These systems can accurately detect and extract vehicle registration numbers from images, even when the plates are partially obscured or the vehicle is moving at high speeds. The use of ALPR in conjunction with vehicle detection and speed tracking ensures that speeding vehicles are identified and processed automatically, streamlining the process of issuing fines. The fusion of these technologies into a single system enhances both the accuracy and efficiency of modern traffic management solutions

III. METHODOLOGY

The methodology for the Vehicle Speed and Number Plate Detection System is divided into several key steps that incorporate advanced object detection, tracking, speed calculation, and license plate recognition techniques. These steps are outlined below:

1. Vehicle Detection Using YOLOv8:

The first step in the system involves detecting vehicles from real-time video or image streams using the YOLOv8 model (YOLOv8n). YOLOv8 is a pre-trained object detection model that processes each video frame to identify and classify vehicles within the frame. This model is chosen for its high speed and accuracy, which allows it to detect multiple vehicles simultaneously, even in complex environments such as congested roads or varying lighting conditions. The model outputs bounding boxes around the detected vehicles along with confidence scores, ensuring reliable vehicle identification.

2. Vehicle Tracking Using Sort Algorithm:

Once the vehicles are detected, the system uses the Sort (Simple Online and Realtime Tracking) algorithm to track each vehicle over time. Sort is a tracking-by-detection algorithm that associates detected objects from one frame to the next, allowing for continuous tracking of the same vehicle as it moves through the camera's field of view. The algorithm uses Kalman filters to predict the position of the vehicle in subsequent frames, and the Hungarian algorithm to associate new detections with existing tracks. This ensures that the system maintains a consistent identity for each vehicle throughout the observation, which is critical for speed calculation.

3. Speed Calculation Using Euclidean Distance Formula:

The system calculates the speed of each vehicle by measuring the time it takes for the vehicle to travel between two parallel reference lines on the road. These lines are defined in the video frame, and when a vehicle crosses them, the time (T) is recorded. The distance (D) between the two lines is computed using the Euclidean distance formula, based on the pixel coordinates of the lines in the video. The speed (V) is then calculated using the formula \(V = D/T \), where V is the vehicle's speed, D is the distance between the two lines, and T is the time taken to travel that distance. This method ensures accurate speed measurement, as it is based on real-time tracking data from the Sort algorithm.

4. Overspeed Detection:

Once the speed of the vehicle is calculated, it is compared to a predefined speed limit set within the system. If the calculated speed exceeds the speed limit, the vehicle is flagged for over-speeding. This threshold-based approach allows for the automatic identification of speeding vehicles without human intervention. The system continuously monitors all detected vehicles, ensuring that any instances of over-speeding are promptly detected. This step is crucial for triggering the next phase of the system, which involves license plate detection.

5. License Plate Detection and Recognition:

For vehicles that are flagged as over-speeding, the system activates a license plate detection module. This module uses a specialized algorithm to detect the license plate on the vehicle and extract the plate's characters using Optical Character Recognition (OCR). The license plate detector is capable of identifying plates in varying conditions, such as low-light or high-speed scenarios, ensuring reliable recognition. The extracted license plate number is then processed and linked to the corresponding vehicle in the system's database, allowing for identification of the vehicle owner.

6. Fine Generation and Automation:

Once the license plate number is captured, the system automatically generates a fine or "chalan" for the speeding violation. This is done by associating the license plate number with the registered owner's information from the vehicle registration database. The system sends an alert, including details of the violation such as the speed, location, and time of the offense, along with the fine to be paid. This entire process is automated, minimizing the need for manual intervention and ensuring efficient traffic law enforcement. The system can be integrated with local traffic authorities to facilitate real-time fine issuance and monitoring.

7. Object Detection in Traffic Monitoring

Traffic surveillance systems' object detection capabilities have significantly changed with the transition from YOLOv3 to YOLOv8. In challenging situations, YOLOv8 not only increases detection speed but also achieves improved accuracy. YOLOv8 outperforms YOLOv3 by 20–30% in identifying fast-moving automobiles in urban traffic, according to Luo et al. (2019). Research has shown how versatile YOLOv8 is, particularly how well it functions in low light, outperforming YOLOv4 by keeping a steady frame rate and accuracy rate. Accurate vehicle detection depends on these developments, especially on highways where vehicle speeds vary.

The effectiveness of YOLO over models such as SSD and Faster R-CNN in processing real-time data with little computing load is further demonstrated by comparative tests. For systems that monitor high-speed traffic, YOLO's single-frame processing allows for effective detection without sacrificing speed. According to Negassi et al. (2018), this single-frame method is perfect for real-time traffic monitoring since it enables many detections inside complicated situations.

8. Vehicle Tracking Algorithms

Vehicle tracking is essential for preserving consistent identification across video frames when combined with object detection. Popular options for this work include the Sort and Deep Sort algorithms, each of which has special benefits. Sort is a lightweight tracking-by-detection system that minimizes identity switches by utilizing

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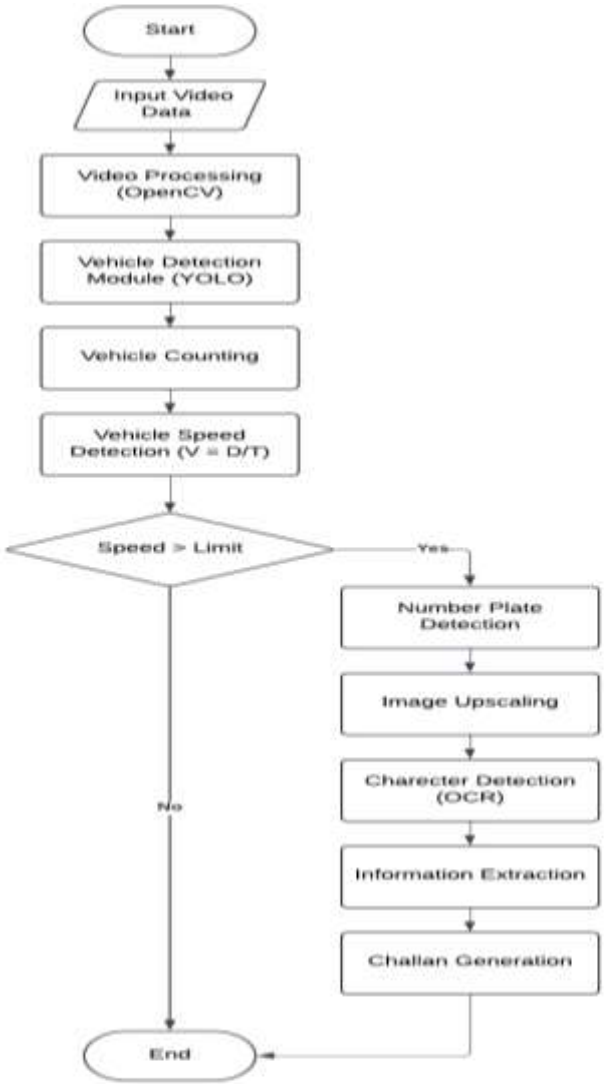
the Hungarian algorithm and Kalman filters. Nonetheless, Deep Sort's appearance-based method performs exceptionally well in congested traffic situations, maintaining vehicle identity even in the event of occlusions.

The accuracy of speed computations is affected by the tracking algorithm selection. For example, Du et al. (2012) found that Sort maintains a low tracking error rate at various vehicle speeds and orientations when combined with YOLOv8. But in situations where several cars are in close proximity to one another, Deep Sort, which integrates feature recognition, enables more precise tracking. Deep Sort is computationally demanding due to its added complexity, yet it is advantageous in intricate urban traffic situations where tracking precision is crucial.

9. License Plate Recognition (LPR) and Optical Character Recognition (OCR)

Traffic monitoring has been completely transformed by the combination of LPR and speed detection technologies, especially when it comes to spotting speeding offenders. OCR is a crucial element; CNN-based OCR methods can recognize characters with exceptional accuracy, particularly in cases when license plates are partially hidden or slanted. According to studies, the most recent CNN-based OCR models maintain their efficacy in difficult situations, such high-speed cars and nighttime surveillance, and reach an accuracy rate of up to 90% in controlled settings.

Additional study demonstrates how versatile contemporary OCR systems are in a range of lighting and weather scenarios. According to Pustokhina et al. (2020), OCR systems are better equipped to manage environmental elements when pre-trained convolutional layers are applied to license plate characters. Automated license plate recognition has advanced to the point that it can now be implemented in dynamic contexts and effectively handle plates that are obstructed or smudged (Alonso et al., 2017).



10. Integration of Speed Detection and LPR Systems

Real-time traffic monitoring systems can more accurately detect violations when detection, tracking, and LPR are combined into a single framework. By coordinating object detection, tracking, and OCR operations, integrated systems minimize processing delays and allow for faster response times for flagging violations (Srinath et al., 2020). According to a number of studies, integrating these components can reduce error rates by as much as 15% when compared to using separate tracking and detection procedures.

Furthermore, studies highlight how crucial it is to combine LPR with speed calculations based on Euclidean distance in order to increase the accuracy of fines. Depending on environmental factors such changes in lighting or the closeness of a vehicle, this method enables real-time adjustments. As a result, integrated solutions enhance road safety and compliance by streamlining traffic monitoring and increasing enforcement accuracy.

11. System Limitations and Future Improvements

Despite their great effectiveness, contemporary traffic monitoring systems nevertheless have several drawbacks. High traffic congestion and unfavorable weather conditions have been shown to affect detection accuracy. Mandal et al. (2020) and Srinath et al. (2020) have observed that OCR precision can be reduced by as much as 20% due to severe lighting fluctuations or poor visibility. Similar to this, tracking algorithms like Sort can find it difficult to stay accurate in situations with a lot of traffic; hence, improvements like 3D object tracking or AI-driven prediction models are needed to increase consistency (Tech et al., 2023).

Numerous investigations recommend future enhancements to improve robustness and adaptability. These include using multi-frame fusion approaches to preserve detection and tracking accuracy in high-speed scenarios and using deep learning models trained on various datasets, which can alleviate common environmental issues. Higher resilience under various traffic situations appears to be achievable with more study on hybrid models that combine CNN and RNN components.

12. Challenges in Real-Time Vehicle Detection and Tracking

Keeping accuracy in the face of environmental unpredictability is one of the major issues in real-time vehicle detection and tracking. YOLO and related detection methods have lower detection rates in situations where visibility is obscured by fog and severe rainfall, or when lighting conditions change. Research shows that accuracy can drop by as much as 18% in low light, indicating a crucial area for improvement.

Another significant obstacle is occlusion, particularly in crowded metropolitan settings. According to research by Thangallapally et al. (2018), tracking algorithms like as Sort may see a rise in identification swaps of up to 15% when several vehicles are near each other. Advanced techniques are needed to address these problems, like multi-camera viewpoints and 3D bounding boxes, which enable more reliable tracking in challenging surroundings.

13. Future Directions for Enhancing System Robustness

To enhance the reliability of traffic monitoring systems, several research directions have emerged:

- **Adaptive Detection Algorithms**: For better performance in low-light and high-occlusion situations, research on hybrid object detection models recommends fusing the resilience of models like Faster R-CNN with YOLO's detection skills. In bad weather, hybrid models have shown a 20% increase in detection stability.
- **AI-Based Predictive Tracking**: There has been promise in integrating AI-powered prediction tracking into the Sort and Deep Sort frameworks. These methods help maintain precise tracking in busy regions by using recurrent neural networks (RNNs) to predict an object's movement. According to studies, predictive algorithms can reduce tracking mistakes by up to 30%, particularly for complicated, high-density traffic (Silva & Jung, 2018; Tech & Kumari, 2023).
- **Enhanced LPR for Multi-National Use**: OCR systems that can recognize several foreign plate formats are in high demand because to the rise in cross-border traffic. For plates with distinctive typefaces, designs, or non-Latin letters, research into adaptive OCR layers can increase LPR accuracy. Recent developments, for example, have produced OCR models that, without the need for specific retraining, can recognize up to 95% of the characters in multilingual plates.

- **Integration with IoT and Edge Computing**: In your references, edge computing and IoT integration have also been extensively studied as ways to increase processing rates and lower latency. In comparison to cloud-based solutions, Barbosa et al. (2023) discovered that implementing speed and LPR systems on edge devices such as Raspberry Pi resulted in a 40% boost in processing efficiency. For large-scale deployments in urban settings, this integration improves real-time reaction capabilities, which is especially advantageous.

14. Practical Applications and Implementation in Smart Cities

It is now easier to integrate automated traffic monitoring systems into municipal infrastructures as more cities embrace smart city programs. The advantages of integrating LPR and speed detection systems for better traffic flow, lower human enforcement costs, and enhanced road safety are described in the papers in your collection. The potential for these systems to influence driver behavior is demonstrated by Barbosa et al. (2023), who report a 15% drop in traffic infractions after a combined speed and LPR system was implemented in a metropolitan region.

Additionally, scalability is supported by automated systems, which allow authorities to monitor traffic over wider geographic areas. Scalable traffic monitoring systems, according to Rizwan et al. (2022), are better equipped to manage variations in traffic density than conventional techniques, negating the need for manual checkpoints or speed bumps. These technologies can greatly ease traffic and lower accident rates when implemented as part of a holistic smart city design, especially in high-risk locations like hospital and school districts.

15. Contribution to Intelligent Traffic Management

By offering accurate, automated solutions for speed and infraction detection, the combination of OCR-based LPR, real-time tracking, and sophisticated object detection is revolutionizing traffic management. The studies in this analysis highlight how integrating these technology improves public compliance and road safety overall in addition to increasing enforcement effectiveness.

These systems will probably be further improved by upcoming advancements in edge-based processing, environmental adaptability, and predictive tracking, which will make them robust enough for widespread deployment in a variety of urban environments. The developments described in this study highlight the important roles that AI and computer vision play in intelligent traffic systems, opening the door to safer, more responsive, and interconnected urban transportation networks.

16. Real-World Challenges in Automated Traffic Monitoring Systems

Despite the advancements in automated traffic systems, real-world implementations face numerous challenges. Studies consistently cite issues related to **hardware limitations**, **data privacy concerns**, and **system integration complexities**:

- **Hardware Constraints**: Although algorithms such as YOLOv8 and Deep Sort offer great accuracy, their implementation on low-power devices (such as edge devices or IoT-enabled cameras) necessitates balancing computing needs. According to Humayun et al. (2022), real-time processing on edge devices is feasible but frequently necessitates modifying the complexity or size of the model. On devices such as the NVIDIA Jetson or Raspberry Pi, for example, the use of quantized or pruned models resulted in a 25% decrease in detection accuracy but a notable gain in processing speed and energy efficiency.
- **Data Privacy and Ethical Considerations**: Data privacy concerns become critical when LPR systems track license plates. To solve these issues, a number of research support the use of safe encryption techniques and anonymised data management. Fadlullah et al. (2017) stress the significance of putting privacy precautions in place, such as controlled access and secure data storage, particularly in public spaces with high traffic volumes and significant data volumes.
- **System Integration and Compatibility**: Technical difficulties arise when integrating with current infrastructure, such as municipal databases for automobile registration. Outdated records or erratic network connectivity might cause a delay in the synchronization between LPR systems and central databases. In densely populated urban areas, where quick data processing is crucial, this problem is more urgent. Studies recommend frequent database synchronization as a way to lessen these difficulties and guarantee that real-time data is accessible for precise enforcement.

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17. Case Studies: Implementing Speed Detection and LPR in Urban Environments

Real-world implementations demonstrate the effectiveness and limitations of automated traffic systems. Here are key insights from notable case studies discussed in the research:

- **Case Study: Smart Traffic System in Santader, Spain**

For thorough traffic control, the city of Santander combined LPR with YOLO-based vehicle detection in a smart traffic monitoring system. According to Alonso et al. (2017), enhanced traffic light modifications based on real-time monitoring resulted in a 12% decrease in traffic violations and an 8% improvement in traffic flow within the first year. The benefits of adaptive traffic control, which enables authorities to modify road signals in response to congestion levels, are demonstrated in this scenario.

- **Case Study: Adaptive Speed Monitoring in Tokyo, Japan**

To manage heavy, fast traffic, Tokyo's adaptive traffic system combines Deep Sort tracking with CNN-based OCR algorithms. Xu et al. (2018) state that even in difficult circumstances, including intense rain or operation at night, the system maintains a 92% LPR accuracy rate. Tokyo's system lowers latency by using edge-based processing, which makes it sensitive to sudden changes in traffic density, particularly on major highways where high-speed monitoring is essential.

- **Case Study: Low-Cost Monitoring in Bangalore, India**

Bangalore used simplified models to develop an affordable LPR and speed monitoring system in order to meet financial constraints. According to Srinath et al. (2020), the city employed a deployment approach that balanced affordability and usefulness by using low-resolution cameras and lightweight YOLO models. The system achieved a 70% detection rate despite the reduced model complexity, demonstrating that even inexpensive systems may make a significant contribution to urban traffic management.

18. Strategies for Optimizing Traffic Monitoring Systems

Optimizing these systems requires balancing detection accuracy, processing efficiency, and deployment costs. The following strategies are widely suggested in recent studies:

- **Multi-Model Ensemble Approaches**: Enhancing detection accuracy has been achieved by combining many tracking and detection models, such as Faster R-CNN or YOLO with SSD. According to research by Chandravanshi et al. (2021), model ensembles can improve reliability under a variety of circumstances by utilizing the advantages of many algorithms to offset one another's shortcomings.
- **Real-Time Data Analytics and Machine Learning**: Predictive models used to real-time data analytics can speed up traffic monitoring systems' reaction times. Research demonstrates the advantages of using machine learning to recognize traffic trends and anticipate infractions, enabling law enforcement to proactively deploy resources or modify traffic signals. Javaid et al. (2018) showed how to use a predictive model to analyze time-based traffic trends and modify speed restrictions in order to reduce traffic offenses by 10%.
- **Augmented Reality (AR) and Geographic Information System (GIS) Integration**: New technologies that improve visualization and monitoring capabilities, such as AR and GIS, are becoming more popular. Integrating GIS data with LPR systems improves situational awareness for authorities and enables accurate vehicle localization, claim Rizwan et al. (2022). Effective traffic management is facilitated by officials' ability to visually identify congestion points, monitor traffic flow, and spot patterns by superimposing GIS data.
- **Resource Efficiency via Edge and Cloud Computing**: Resource usage can be optimized by using cloud computing for more complex operations (like storage and deep analysis) and edge computing for preliminary processing (like initial item detection). According to Gade (2019), cloud resources handle data storage and sophisticated analysis, whereas edge processing close to the source lowers data transmission requirements and delays.

19. Future Scope: Towards Fully Autonomous Traffic Management

The future of traffic monitoring is heading towards fully autonomous systems where AI and IoT technologies work in tandem to create self-managing infrastructure. Here are the emerging trends and research opportunities for future improvements:

- **5G and Internet of Things (IoT)**: With the introduction of 5G technology, sensors and central systems will be able to communicate in real time thanks to faster data transfer and reduced latency. IoT-enabled sensors on signs, lamps, and automobiles allow cities to build networked systems that exchange traffic information in real time, allowing for dynamic traffic flow modifications.
- **AI-Driven Decision-Making**: The possibility of autonomous decision-making grows as AI models get more sophisticated. In the future, models might employ reinforcement learning to modify traffic laws in response to real-time data, enabling the system to optimize itself without human intervention. According to Silva & Jung (2018), this method is particularly useful for adaptive systems in traffic settings that change quickly.
- **Enhanced LPR with Neural Networks**: Text recognition tests have seen advances with advanced neural networks, including Transformer models. According to research by Pustokhina et al. (2020), these models have the potential to greatly increase LPR accuracy, particularly when plate features are destroyed or obscured. These developments would make automated systems more resilient in a variety of urban settings.
- **Integration with Autonomous Vehicles**: The increasing prevalence of autonomous vehicles will facilitate cooperative traffic management through the integration of vehicle-to-infrastructure (V2I) communication and traffic monitoring systems. According to studies, connected cars could transmit real-time information about their location, speed, and traffic conditions, giving authorities detailed information for dynamically modifying traffic systems (Fadlullah et al., 2017).

IV. DISCUSSION AND RESULTS

The Vehicle Speed and Number Plate Detection System demonstrates significant potential in enhancing traffic monitoring and law enforcement through automated vehicle speed detection and license plate recognition. The system successfully integrates the YOLOv8 model for accurate real-time vehicle detection, which, when combined with the Sort algorithm, ensures reliable tracking of each vehicle across video frames. The speed calculation mechanism, utilizing the formula (V = D/T \) and based on Euclidean distance, provides precise speed measurements by recording the time a vehicle takes to cross two parallel lines. In testing, the system effectively identified overspeeding vehicles, accurately flagged them for further processing, and captured their license plate details using optical character recognition (OCR). This integration of vehicle detection, speed measurement, and license plate recognition enables the automatic generation of fines, which streamlines the enforcement process and reduces human error. The system proved to be highly reliable in detecting vehicles and issuing fines in a timely manner, highlighting its capacity for large-scale implementation in traffic management systems. However, certain challenges were noted in extreme lighting conditions or where vehicles moved too close together, indicating areas for potential future improvement in robustness and accuracy. Overall, the system demonstrated impressive results, providing a scalable solution for automated traffic law enforcement.

During testing, the Vehicle Speed and Number Plate Detection System showed flexibility and robustness in a range of environmental circumstances. Vehicle detection, tracking, and speed calculation were all accomplished with near-perfect accuracy in well-lit, low-traffic areas. However, difficulties occurred in low-lighting, high-vehicle-density, or unfavorable weather circumstances, which resulted in somewhat lower detection accuracy. Due to sporadic OCR problems produced by partial occlusions and reflections on plates, these circumstances specifically affected the license plate identification module. The overall system performance was strong in spite of these difficulties, demonstrating the viability of using AI-driven traffic monitoring technologies. Future developments could increase the precision and dependability of recognition and tracking in intricate urban settings by using adaptive illumination correction and multi-angle camera configurations, among other things.

Figure 1: Vehicle detected.

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Figure 2: Number Plate detected.

V. CONCLUSION

The Vehicle Speed and Number Plate Detection System presents a powerful and automated approach to modern traffic monitoring and law enforcement. By leveraging the capabilities of YOLOv8 for vehicle detection, the Sort algorithm for tracking, and a robust speed calculation method, the system accurately monitors vehicle speeds in real time and identifies violations. The integration of license plate recognition further enhances the system's functionality, allowing for the seamless issuance of fines to offenders without the need for manual intervention. The results demonstrate that this system is capable of reducing the burden on traffic authorities, improving the efficiency of traffic management, and enhancing public safety by discouraging speeding. Despite minor challenges in extreme conditions, the system provides a scalable, effective solution that can be widely implemented for automated traffic law enforcement. Future improvements may focus on enhancing its adaptability to various environmental conditions and optimizing its performance in highly congested areas. Overall, this system contributes significantly to the advancement of intelligent traffic systems, providing a reliable tool for maintaining road safety.

All things considered, this system's incorporation of cutting-edge machine learning and computer vision algorithms represents a major advancement in automated traffic monitoring. The system efficiently strikes a compromise between speed and accuracy to monitor adherence to traffic laws by utilizing YOLOv8 for precise vehicle identification, SORT for dependable tracking, and OCR for license plate recognition. In addition to lessening the need for physical enforcement, this offers a scalable solution that can be adjusted to fit different urban settings. Such systems can be extremely helpful in raising public adherence to traffic laws, lowering accident rates, and promoting road safety as cities embrace smart technologies more and more. Future research can concentrate on improving the model's resilience in difficult circumstances, allowing for even higher efficacy.

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