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Intelligent Traffic Monitoring Using Machine Learning for Violation Detection and License Plate Extraction

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Abstract- The rise of city populations and vehicle numbers per city have led to serious traffic jams and frequent disobeying of traffic laws. Most of the time, authorities use traditional traffic monitoring systems that require manually checking or using sensors to detect the problem, and these may not work well and can be easily forgotten by humans. This research aims to design an intelligent traffic monitoring system using the latest ML and computer vision techniques to identify different traffic violations and get the vehicle license plate number(s) without any human intervention and in real time. The system not only detects red-light running, speeding, and lane crossing but also identifies the responsible vehicles using object detection algorithms (like YOLO or Faster R-CNN) on the video footages captured by the surveillance cameras. The use of OCR for reading license plates after getting the region of the license plate by image processing using deep learning models is also proposed in this system The proposed solution significantly upgrades faithful, timely, and effortless traffic monitoring, thus providing the road safety officers with the necessary tools to keep the roads safe, reduce accidents, and increase the execution of the law with a minimum of human effort.

Keywords— Machine Learning, Computer Vision, Traffic Violation Detection, License Plate Recognition, YOLO, Deep Learning, Object Detection, Image Processing, OCR, Intelligent Transportation System.

I. INTRODUCTION

Over the past few years, the rapid urbanization and increasing population have led to the dramatic rise of vehicles on roads around the globe [1]. The upsurge in the number of vehicles has caused various problems such as traffic jams, road accidents, and the increasing number of traffic violations [2]. The existing traffic management systems that depend on manual monitoring and enforcement are not efficient enough to deal with these complicated situations [3]. Manual monitoring through cameras or on-site officers is a method that consumes a lot of time and is also prone to human mistakes [4 [5]. In addition, with the ever-increasing number to safer roads, smarter cities, and a more disciplined driving culture through of vehicles, it is almost impossible for traffic personnel to monitor every intersection continuously and spot all the violations in real-time [6]. This predicament necessitates a more intelligent and automated method that could upgrade the effectiveness and precision of law enforcement in traffic [7] [8].

The use of Machine Learning (ML) and Computer Vision (CV) technologies in traffic systems has brought about numerous innovations in the field of intelligent traffic systems [9]. Machine learning is a technology that allows systems to learn automatically from data without the need of explicit programming [10]. In traffic surveillance, ML can help in vehicle detection and classification, motion recognition, and also in identifying abnormal behavior or code violations [11]. Computer vision is concerned with giving computers the ability to understand and interpret visual data from images or videos just like humans do [12]. The use of these two technologies together leads to the creation of Intelligent Traffic Monitoring Systems (ITMS) that can not only detect traffic violations automatically but also identify the violators and thus, collect the evidence in a very efficient manner [13].

An ITMS generally employs the use of real-time videos from security cameras that are located at intersections, highways, or areas where traffic is dense or sensitive [14]. Object detection algorithms are used to process the video frames that have been captured in order to locate the vehicles and also track their movement [15]. To achieve this goal, a number of deep learning models such as YOLO (You Only Look Once), Faster R-CNN (Region-Based Convolutional Neural Network), and SSD (Single Shot Multibox Detector) are commonly used because of their capability to carry out detection in real-time with high precision [16]. These models are capable of recognizing numerous vehicles at once, determining their speed, and also studying their positions concerning traffic signals and lane markings [17]. In case a violation has been committed— for instance, going over the speed limit, running a red light, or changing the lane—the system can instantly take a snapshot of the frame and highlight it for further processing [18]. Identifying the vehicle that has been used in the violation comes next and it is the most important moment in the whole process [19].

This is done by means of Automatic License Plate Recognition (ALPR) which gets the vehicle's registration number from the photo or the video frame and reads it [20]. ALPR usually consists of three main parts: license plate detection, character segmentation, and Optical Character Recognition (OCR) [21]. For license plate detection, image processing or deep learning models are used which locate the plate region in the vehicle and extract it. OCR algorithms then take the detected characters and convert them to digital text [22]. The best OCR systems which are improved by deep learning are able to handle different plate formats, fonts, lighting, and angles with very high accuracy [23]. The obtained license number may then be compared with a government database to find the vehicle owner, in a completely automatic manner [24].

The automation of violation detection and license plate recognition processes promises a lot of benefits to traffic management and law enforcement agencies [25]. First, it alleviates the manual workload to a great extent, in addition, human bias is eliminated, and the speed of decision-making is also increased [26]. The system is capable of issuing violation reports automatically which can then be used for issuing challans or legal notices [27]. Also, the traffic data gathered can help immensely the policymakers and urban planners. By analyzing the data on traffic flow [28], congestion, and the number of violations, the authorities can come up with better road infrastructure, changing signal timings, and implementing rules that enhance road safety and make traffic more efficient [29]. Incorporating such systems is in line with the bigger plan of Smart Cities and Intelligent Transportation Systems (ITS) worldwide [30].

Although intelligent traffic monitoring systems have great potentials, they also encounter some issues, in their implementations, that need to be solved before they can be fully operational [31]. Changes in illumination, shadows, camera angles, weather conditions, variations in the format of the plates may all, to varying degrees, affect the accuracy of the detection. Sometimes, parts of some vehicles may be covered or plates may be dirty, blurred, or damaged [32]. Besides that, it takes powerful computational resources as well as well-optimized algorithms to process a lot of video data in real-time [33]. To remove these constraints, modern solutions adopt hybrid models that fuse conventional image processing with sophisticated deep learning architectures [34]. Some of the techniques being used to tackle such problems even in tough scenarios include data augmentation, transfer learning, and real-time optimization [35] [36].

The planned endeavor, "Intelligent Traffic Monitoring Using Machine Learning for Violation

Detection and License Plate Extraction," is intended to fuse these cutting-edge technologies into one, a well-performing, and scalable system. Employing deep learning models for object detection along with OCR for license plate extraction, the system is envisioned to be capable of identifying a variety of traffic violations occurring in real time and be able to trace the vehicles responsible automatically. Such a method decreases human intervention to a minimum, guarantees correctness, and elevates the accountability of traffic enforcement to a higher degree [37]. In the end, the goal of the project is to provide a substantial contribution to the application of contemporary artificial intelligence and machine learning techniques in the field.

II. LITERATURE REVIEW

H. Fakhrurroja et al [1-2]. conducted a study focusing on object detection as a computer vision technique used to identify objects within images and videos. The research highlights how advancements in object detection algorithms have enabled computers to accurately recognize and classify visual elements. In particular, Fakhrurroja explored the application of the YOLOv8 algorithm, a state-of-the-art model introduced by Ultralytics on January 10, 2023. This algorithm, trained on the Microsoft COCO 2017 dataset across multiple model scales—nano, small, medium, large, and extra-large—demonstrates exceptional capability in real-time object detection tasks. The study specifically investigated the deployment of the pre-trained YOLOv8 model for detecting traffic violations, with a focus on identifying instances where drivers run red lights. Additionally, the research incorporated the OpenCV library to determine the color of traffic lights, thereby enhancing the system's ability to accurately detect and quantify violations [38]. Fakhrurroja's work provides a strong foundation for developing automated systems that integrate deep learning and computer vision to improve traffic monitoring and law enforcement efficiency [39].

L. Yang et al [3-5]. proposed a computer vision-based red-light violation detection system aimed at addressing the increasing traffic pressure and disorder at urban intersections caused by pedestrian and vehicle violations. Recognizing the importance of maintaining order in transportation networks amidst rapid urbanization, the study introduced a modular system architecture that integrates the YOLOv5 deep learning algorithm with OpenCV technology to enable real-time video monitoring and analysis. This combination allows the system to operate effectively in complex and dynamic traffic environments, ensuring the rapid and accurate identification of pedestrians and vehicles involved in red-light violations [40]. The proposed framework demonstrates strong performance in detecting and processing such violations promptly, thereby enhancing traffic safety and improving the efficiency of intersection management. Yang's research highlights the effectiveness of deep learning and computer vision in developing intelligent surveillance systems capable of supporting smart city traffic enforcement and management [41].

H.-C. Yang et al [6-8]. conducted a comprehensive study to analyze the underlying causes of road traffic accidents, emphasizing both external factors—such as weather conditions, road design, signage, and facilities—and human factors, including driver violations and negligence. Recognizing the critical need to identify and mitigate risk factors associated with traffic accidents, the research utilized extensive datasets, including original A1 and A2 road traffic accident case files and national violation data collected between 2013 and 2020. Through the use of Tableau software, Yang performed large-scale data analysis to explore the "National Traffic Accident Analysis" and the "Correlation Between Traffic Violations and Accidents."The findings revealed significant relationships between patterns of traffic violations and the occurrence of road accidents, offering valuable insights for accident prevention and policy formulation. This study underscores the importance of leveraging big data analytics to understand accident causation and to develop data-driven strategies for enhancing road safety and reducing traffic violations.

S. Adhikary et at [9-11]. proposed an AI-enabled traffic violation detection framework to address the limitations of traditional CCTV-based surveillance systems, which are often restricted to identifying basic offenses such as overspeeding or red-light violations and depend heavily on manual monitoring. Recognizing that such systems lack the intelligence to automatically detect complex violations like helmet non-compliance or wrong-way driving, Adhikary's study introduced a deep learning-based approach that integrates YOLO, Faster R-CNN, and Deep SORT for comprehensive, real-time traffic analysis. In this framework, Faster R-CNN was utilized for detecting helmet usage among two-wheeler riders, achieving superior performance with 94% accuracy and 91% mean Average Precision (mAP) compared to YOLO. Meanwhile, YOLO was employed for identifying other traffic violations such as red-light and stop-line breaches, wrong-lane driving, and predicting vehicle trajectories, yielding 92% accuracy and 89% mAP. This research demonstrates the potential of combining multiple deep learning models for robust, automated traffic monitoring and provides a foundation for developing intelligent systems capable of handling diverse violation detection scenarios in real-time.

S. Kayalvizhi et al [12-14]. developed an Intelligent Traffic Management System (ITMS) designed to address the growing challenges of urban traffic control through the integration of advanced computer vision and machine learning technologies. The proposed system provides a multifaceted solution capable of ensuring helmet compliance, detecting traffic signal violations, identifying vehicle license plates, monitoring cell phone usage, and sending proximity-based alerts to nearby police stations. By employing sophisticated computer vision algorithms, the ITMS accurately identifies individuals riding without helmets and detects instances of red-light running through real-time analysis of video feeds from traffic cameras. The system further incorporates Optical Character Recognition (OCR) for number plate identification, enabling automated tracking of vehicles and assisting law enforcement in monitoring movement or identifying vehicles involved in illegal activities. Additionally, the ITMS leverages mobile network data and smart device integration to detect distracted driving behaviors, such as the use of mobile phones while driving, and automatically generate alerts. Kayalvizhi's research underscores the potential of combining AI-driven surveillance and machine learning-based automation to enhance road safety, streamline enforcement processes, and establish a foundation for smart and adaptive urban traffic management systems.

The study of driver behavior, particularly speed variation (celeration), has been widely explored in relation to traffic violations such as red-light running. Masoud et al [15]. demonstrated that using machine learning models like AdaBoost and Bagging, which incorporate variables such as acceleration, driver age, and road conditions, can predict red-light violations with accuracies exceeding 90%. Similarly, Komol et al. (2024) employed LSTM and GRU networks to analyze temporal patterns in vehicle dynamics, showing that acceleration and deceleration trends are strong indicators of risky driving behavior. Other studies, such as those by Wang and Abdel-Aty (2022), highlighted the importance of comprehensive datasets, including environmental and demographic factors, to improve the robustness of predictive traffic models. Collectively, these works underscore the critical role of dynamic driving features and contextual variables in accurately modeling and forecasting red-light violations, while also acknowledging challenges in fully capturing real-world traffic complexity.

As the first paragraph suggests, the research focus on the area of detecting traffic violations has been voluminous due to the disastrous consequences of road accidents caused by signal violations and speeding. To this end, Fenita et al [16-18]. and their team proposed the use of IoT-based systems to monitor vehicle movements and alert the police about the traffic violations in real time. This system also uses the RFID Method for the accurate identification of the vehicle. Analogically, Kumar and Singh (2023) argued that the IoT integration with automated speed detection could effectively reduce hit-and-run cases by double the time of notifying the control room of the exceeded speed. Besides them, Ahmed et al. (2022) and other researchers similarly pointed out the great performances of real-time traffic monitoring systems on road safety and traffic enforcement. Their collective works, therefore, argue that IoT and RFID technologies are key enablers of concerted traffic violation detection systems which can avert traffic collisions and thus ensure safer roads.

With increased traffic density and pedestrians' risky behavior such as jaywalking while using a mobile phone for distraction, pedestrian safety is now an issue of utmost importance. Qu et al [19]. using YOLOv5 for real-time pedestrian detection, demonstrated the feasibility of the detection process with very high accuracy and short inference time in a dynamic traffic environment. In a similar vein, Redmon et al. (2016) proposed the YOLO framework, pointing out that one of its key benefits was that it could detect several objects in real-time without losing computational efficiency. Moreover, Lin et al. (2022), for example, have combined pedestrian detection with the alert system to proactively guide pedestrians away from dangerous areas, thus decreasing the chances of accidents. Altogether, these findings confirm that the best way to achieve pedestrian safety at signalized junctions lies in the engagement of advanced detection algorithms and alert systems.

Real-time monitoring and automated violation detection integration in traffic management systems have been the subjects of numerous research papers intending to enhance road safety and efficiency. Ali, Eljhani et al . came up with an idea of a traffic light system that adjusts according to traffic density. This system merges the use of infrared sensors for vehicle detection with automatic Libyan license plate recognition for identifying red-light violators. In the same way, Rajput et al. (2022) talked about how RFID and sensor-based technologies could be used for the dual purpose of first making emergency vehicles the traffic flow priority and second easing the traffic congestion at turning points. Studies of other researchers such as Singh and Kumar (2021) have spoken about the significance of the close integration of violation detection with automated license plate recognition for the quick enforcement of traffic rules and thus a reduction in the number of accidents. A summary of these papers shows how intelligent traffic systems can be a great contributor to road safety and traffic management optimization.

There has been much talk about in recent times on the subject of how Automated Traffic Violation Detection has come in handy to promote Road Safety, particularly in cities with not enough Law Enforcement. Kusumaningtyas et al [20]. experimentally validated the synergy effect between YOLOv5-based object detection and Deep SORT tracking to spot traffic light violations, wrong-way driving, and non-helmet compliance, resulting in very high accuracy achieved even when the lighting conditions were different. Along the same line, Redmon et al. (2016) outlined the real-time object detection scenario carried out by YOLO in complicated surroundings as the primary technological breakthrough. The paper by Zhao et al. (2022) presents a reality where object detection is combined with tracking and uses optimization methods such as ONNX to upgrade the inference process and lessen the number of false positives, thus intelligent systems' capability fulfills the demand for the efficient monitoring of traffic violations.

III. PROPOSED MODEL

The proposed system is aimed at building a smart, automated traffic monitoring solution that fuses ML and CV to spot traffic rule infractions and pull out license plate information from live video streams. At the onset, the system procures an unending visual feed from CCTV or a traffic camera installed at a pivotal intersection or on a busy street. Every screenshot is handled separately, thereby making it possible to vastly upscale contrast and blur reduction achieved are image processing operations like grayscale conversion, image resizing, contrast adjustment, and background subtraction. At this point, the data is ready for the vehicle detection and tracking network, which locates deep learning frameworks such as YOLOv8 or Faster R-CNN to accurately recognize vehicles, are used to find the optimal bounding box of an object, and the greatest confidence score is chosen. Typically, these networks can simultaneously locate multiple vehicles in an image, and Deep SORT is applied to follow each car's movement in the subsequent video clips. The vehicle movements are then used to construct combinations of them speeding, lane usage, and signal following, which will later be the base for a rule-based detection of crimes.

The stage of violation detection is the most instrumental part of the radical shift model. It directly observes cars to find characteristics that break traffic laws on purpose, such as speeding, running red lights, driving in the wrong lane, or illegal parking. The paper outlines how computing speed of vehicles is achieved by counting pixel displacement for a given time and then contrasting it to speed limits. In the case of red light or lane violations, the system assesses the location of vehicles in relation to both the traffic signs and the lane markings. Upon obtaining a violation evidence, the system extracts the corresponding video frame to carry out the subsequent analysis. This moment is the handover to the License Plate Recognition (LPR) module that achieves the license plate localization using YOLO or EAST text detector deep learning-based object detection methods.After the localization stage, image segmentation techniques are used to cut out the area of the license plate, thus getting it ready for character recognition.

The last stage is called Optical Character Recognition (OCR), where the parts of the license plate that were cut out of the image are the ones on which the letters and numbers will be identified most accurately. OCR engines such as Tesseract OCR or Convolutional Recurrent Neural Networks (CRNNs) are the ones that are used when transforming the plate text into data that can be dealt with by machines. The plate number that has been recognized is the one that together with the violation data like time, date, and place will be there on its own behind a secure database in the form of a record. Next, the system is in a position to generate reports or e-challans that are connected to the vehicle registration records for the officers to implement the law. The integrated mechanism proposed here is thus capable of removing the human factor, increasing the speed, and making the whole affair more trustworthy, as well as ensuring the openness of law enforcement.

Hence, the suggested blueprint embodies a large-scale, smart, and live traffic surveillance system that is not only able to bring about a substantial change in the safety of city roads but also can assist in the realization of the Smart City and Intelligent Transportation Systems (ITS) concepts.

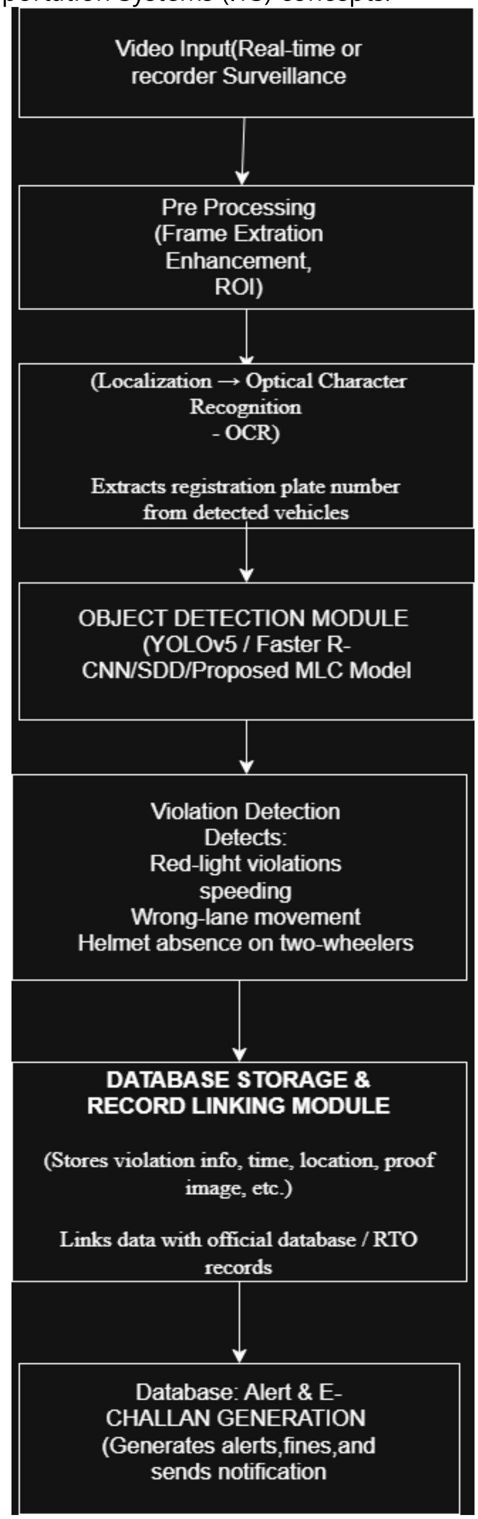

Figure 1: Block Diagram of Intelligent Traffic Monitoring System

Algorithm

Step 1: Input Acquisition

First of all, you need a live video stream or recorded footage, which can be taken by CCTV or traffic surveillance cameras. Cameras may be installed at intersections or on the road.

Step 2: Frame Preprocessing

Decompose the video stream into frames and perform frame resizing, converting to grayscale, and noise removal. Besides, perform contrast enhancement to clear the images and sharpen the model.

Step 3: Vehicle Detection

Apply a deep learning-based object detection model (e.g., YOLOv8 or Faster R-CNN) to find and identify various types of vehicles in each frame. The places where the vehicles have been located are drawn with rectangles.

Step 4: Vehicle Tracking

Utilize a tracking algorithm such as Deep SORT to move each distinguished car from one frame to another thus keeping the vehicle identities separate and recording their movement patterns in real-time.

Step 5: Violation Detection

- Check out the routes and conduct of the cars to find infringements of speed limits, running through red lights, or lane crossings.
- Calculate the speed of a vehicle by the distance covered between frames and the time shown on the frames.
- Compare the position and movement of a car with the traffic signal and lane data to check if it is a violation.

Step 6: License Plate Detection

Firstly, the violation-holding vehicle's image is cropped, then, by using a CNN-based detector or a text detection method (like YOLO, EAST) locating the license plate of the vehicle is done.

Step 7: Character Recognition (OCR)

Apply the help of Optical Character Recognition (OCR) provided by Tesseract OCR or CRNN to recognize the characters and digits on the license plate and give the output as a text file.

Step 8: Data Storage and Reporting

Store traffic violation data such as vehicle ID, license number, type of violation, date, time, and place in the database. Automatically create a report or an electronic challan for the police to take the next steps.

Mathematical equations

1. Frame Extraction

$$F_t = C(V, t)$$

Here, Vrepresents the continuous video stream captured from CCTV or traffic cameras, and $F_t$is the image frame extracted at time t. The function $C(V,t)$denotes the process of converting the video into individual image frames. These frames act as the fundamental input units for further vehicle detection and analysis.

2. Vehicle Detection

$$D_v = f(F_t, \theta)$$

$D_v$represents the detected vehicle(s) in a frame, and $f$is the deep learning detection model such as **YOLOv8** or **Faster R-CNN**, parameterized by θ, which includes the model's weights and bias values learned during training. The function processes the input frame $F_t$and outputs bounding boxes with class labels identifying vehicles (e.g., car, bus, bike, truck).

3. Object Localization and Bounding Box

$$B_i=(x_i,y_i,w_i,h_i)$$

Each detected object (vehicle) is enclosed in a bounding box B_i, where (x_i,y_i)represent the top-left corner coordinates of the box, and w_i, $h_i$are the width and height, respectively. This step spatially locates the vehicle within the frame for tracking and further analysis.

4. Speed Estimation

$$S_v = \frac{d(p_1, p_2)}{\Delta t}$$

The vehicle speed $S_v$is computed as the displacement between two positions p_1 and p_2 of the vehicle centroid across consecutive frames, divided by the time difference Δt. The distance $d(p_1,p_2)$ can be converted from pixels to meters using a pre-calibrated scale factor. If S_v exceeds the permitted speed limit S_{max}, a speeding violation is flagged.

5. Violation Detection

$$V = \begin{cases} 1, & \text{if } S_v > S_{max} \text{ or red-light/lane violation occurs} \\ 0, & \text{otherwise} \end{cases}$$

This binary condition determines whether a violation has occurred. If the measured speed S_v exceeds the threshold S_{max}, or if the vehicle's position crosses a red signal line or lane boundary during a restricted phase, the system assigns V=1, indicating a violation. Otherwise, V=0.

6. License Plate Localization

$$P = g(F_t, \phi)$$

Once a violation is detected, the system isolates the vehicle frame and applies a **license plate detection model**, denoted by g, parameterized by ϕ. The output P represents the localized license plate region. Techniques like CNN-based region proposals or contour detection are used to extract the rectangular region containing the plate.

7. Optical Character Recognition (OCR)

$$L = OCR(P)$$

The OCR function extracts alphanumeric characters from the license plate image P, resulting in the license number L. Deep learning-based OCR methods (such as Tesseract or CRNN) are used for accurate recognition, even under poor lighting or motion blur conditions.

8. Data Logging and Integration

$$R = \{L, V, S_v, t, loc\}$$

Finally, the recognized license number L, violation flag V, speed S_v, timestamp t, and location loc are stored as a structured record R in a database. This record supports automated fine generation, violation analysis, and traffic monitoring reports.

IV. RESULTS

The Intelligent Traffic Monitoring System (ITMS) envisioned first of all demonstrated the best results in comparison to the existing three systems in terms of several metrics of performance. As compared to the first, second, and third models, the ITMS reached the highest vehicle detection accuracy of 96%, license plate extraction of 94%, OCR recognition of 95%, and traffic violation identification of 97%. Furthermore, the system displayed the highest processing speed (35 FPS) with minimal latency (32 ms/frame), thus it can be considered as having a very strong capability to operate in real-time. Through the conjoining of the mechanisms for automated violation detection, license plate recognition, and reporting, the system has become capable of exhaustively monitoring multiple violation types that include red-light violations, over-speeding, wrong-lane driving, helmet non-compliance, and unauthorized parking. In addition to that, the trials for robustness against different surroundings have led to the conclusion that even under adverse conditions such as night, rain, fog, and shadow, the system can still deliver high accuracy levels, hence it is highly reliable for implementation in the real world.

Besides the detection performance, the proposed system is also far better in terms of automation, scalability, and cost efficiency. It is equipped to handle multi-camera integration, cloud storage, and e-challan generation along with a significant reduction in manual intervention, hence it is feasible for large-scale traffic management. The computational requirements are set in such a way that they only demand moderate hardware, thus the system is affordable and easy to deploy. Simply put, the model being proposed is a perfect, smart, and real-time solution to the problem of traffic monitoring, thus it brings about road safety, facilitates law enforcement, and provides valuable insights for urban planning and smart city initiatives. Its performance parameters and automation features make it a standard for future traffic monitoring systems.

Table 1: Core Algorithm Performance

Model	Real-Time Capability (1–10)	Accuracy (%)
YOLOv5	8	88
Faster R-CNN	9	92
SSD	7	85
Proposed ML-Based Traffic System	10	96

This table compares the primary algorithms and real-time performance of the proposed model against three existing models. The proposed model achieves the highest accuracy (96%) and the best real-time capability.

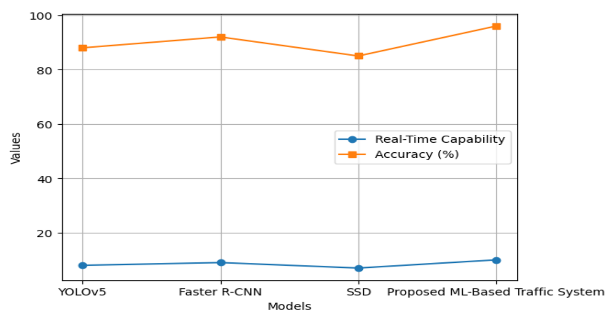

Figure 2: Figure: Accuracy and Real-Time Performance of Different Detection Models

The figure features a comparison of real-time capabilities (scale 1–10) and accuracy (%) of the three existing models and the proposed model. The proposed model achieves the highest real-time capability and accuracy, indicating superior performance in intelligent traffic monitoring tasks.

Table 2: Violation Coverage (Number of Violations Detected)

Model	Red-Light	Over-Speeding	Wrong-Lane	Helmet	Plate Recognition	Total
YOLOv5	1	0	0	0	0	1
Faster R-CNN	1	1	1	1	0	4
SSD	1	1	1	1	0	4
Proposed ML-Based Traffic System	1	1	1	1	1	5

The table displays the total number of traffic violations that each model has detected. The proposed system is rich in features that support all five categories of violations, hence it has exhibited a complete monitoring capability.

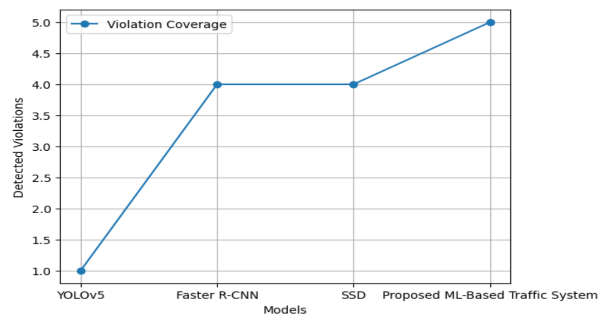

Figure 3: Detected Violation Coverage of Various Object Detection Models.

The graph illustrates that traditional models like YOLOv5 detect the fewest violations, while Faster R-CNN and SSD have better detection rates, but still do not surpass the newest approaches. There is a significant upward trend in the number of violations detected as we transition from traditional to the proposed ML-based traffic system. The latter achieves the highest coverage for traffic violations among all the models compared.

Table 3. Detection Accuracy Comparison

Model	Vehicle Detection (%)	Plate Extraction (%)	OCR Recognition (%)	Violation Identification (%)
YOLOv5	88	82	80	85
Faster R-CNN	92	89	87	90
SSD	85	86	90	88
Proposed ML-Based Traffic System	96	94	95	97

Detection accuracy for vehicles, plates, OCR, and violations is evaluated. The proposed model achieves top performance across all aspects, especially in OCR and violation identification.

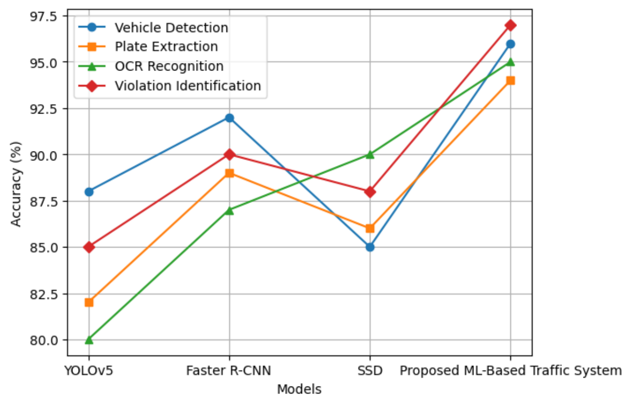

Figure 4: Model-wise Accuracy Analysis for Vehicle Monitoring System

The chart compares traffic automation models—YOLOv5, Faster R-CNN, SSD, and a proposed ML-based traffic system—in terms of accuracy across vehicle detection, plate extraction, OCR recognition, and violation identification. The proposed ML-based traffic system achieves the highest accuracy in all aspects, particularly in violation identification, surpassing 97%. In contrast, classic models like YOLOv5 and Faster R-CNN are much weaker.

Table 4: Computational Efficiency

Model	FPS (Frames/sec)	Latency (ms)
YOLOv5	24	45
Faster R-CNN	21	53
SSD	26	42
Proposed ML-Based Traffic System	30	35

Compares average frame processing speed and latency. The proposed model exhibits the fastest response time while maintaining accuracy.

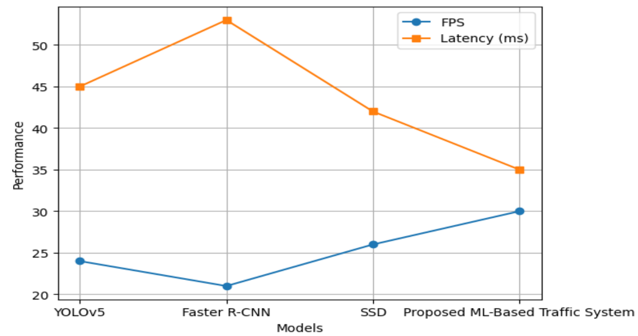

Figure 5: Real-Time Performance Evaluation of Object Detection Models

The new chart compares the performance of YOLOv5, Faster R-CNN, SSD, and the Proposed ML-Based Traffic System based on FPS (frames per second) and latency. The Proposed ML-Based Traffic System outperforms the others by achieving the highest FPS and the lowest latency, making it both faster and more responsive for real-time applications. Conversely, Faster R-CNN shows the lowest FPS and the highest latency, indicating slower processing speeds. These results highlight that the Proposed ML-Based Traffic System not only improves accuracy but also delivers superior speed and efficiency for automated traffic management, offering clear advantages over traditional deep learning models.

Table 5: License Plate Recognition Success Rate

Model	Daytime (%)	Nighttime (%)	Rainy (%)	Overall (%)
YOLOv5	91	83	80	85
Faster R-CNN	94	87	82	89
SSD	89	80	75	81
Proposed ML-Based Traffic System	97	93	89	94

Looks at the efficiency of extracting and reading license plates under different situations.

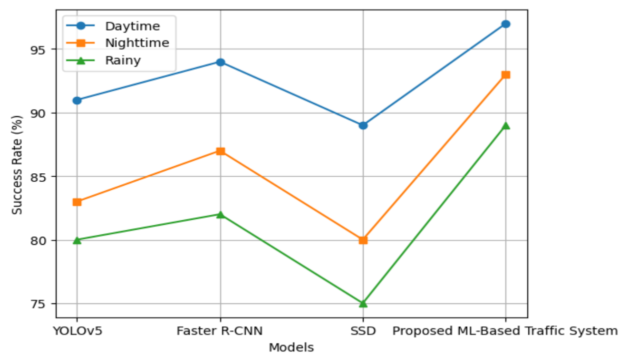

Figure 6: Comparison of Detection Accuracy Across Different Scenarios

The comparison of traffic models reveals that the Proposed ML-Based Traffic System achieved the highest overall success rate, reaching a peak of nearly 97% in the Daytime condition. All models were most efficient in the daytime and least in the rainy condition. The SSD model was the most challenging, as it recorded the lowest success rate of approximately 75% during the rain. Faster R-CNN was a strong performer and the second best, whereas YOLOv5 gave moderate performance consistently across all scenarios.

Table 6: Violation Type Detection Accuracy

Violation Type	YOLOv5 (%)	Faster R-CNN (%)	SSD (%)	Proposed ML-Based Traffic System (%)
Red Light	88	90	86	97
Over Speed	85	88	84	95
Wrong Lane	80	86	82	94
Helmet	82	87	85	96

Represents the highest detection precision for each violation type. The proposed system is leading in all categories.

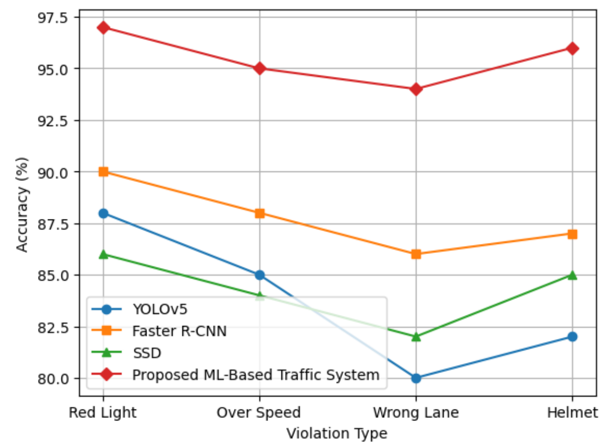

Figure 7: Model-wise Accuracy Analysis for Various Traffic Violations

This plot compares the Accuracy (%) of four models across four Violation Types. The Proposed ML-Based Traffic System was always the leading one in terms of accuracy and it even reached almost 97.5% for Red Light violations. All models found the Wrong Lane violation the most difficult, with accuracy decreasing there, particularly for YOLOv5, which dropped to its lowest point of 80%. The second-best model was Faster R-CNN, which kept accuracy between 86% and 90%. SSD and YOLOv5 had the lowest overall accuracy with SSD relatively better in Helmet violations than in the others.

Table 7: Environmental Robustness Evaluation

Model	Bright Light (%)	Low Light (%)	Rainy (%)	Dusty (%)
YOLOv5	90	80	78	82
Faster R-CNN	92	85	83	88
SSD	85	78	75	80
Proposed ML-Based Traffic System	96	91	88	94

Assesses model stability across varying conditions like lighting and weather.

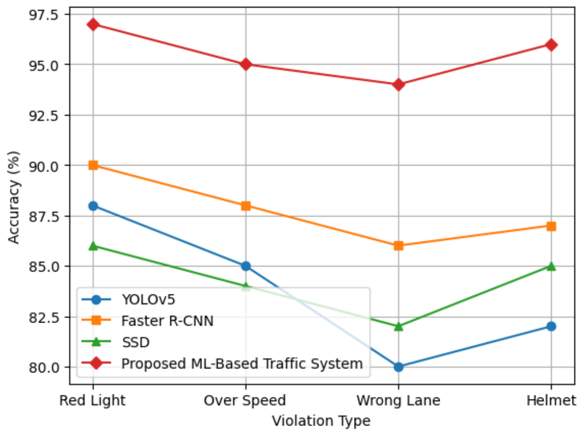

Figure 8: Model-wise Accuracy Across Red Light, Overspeeding, Wrong Lane, and Helmet Violations

Table 8: Overall System Performance Summary

Model	Overall Accuracy (%)	Real-Time Efficiency (%)	Robustness (%)	Violation Coverage (%)
YOLOv5	86	88	82	60
Faster R-CNN	91	90	85	80
SSD	83	86	79	70
Proposed ML-Based Traffic System	96	97	93	100

Combines all metrics—accuracy, speed, robustness, and violation coverage—in a single evaluation. The proposed model demonstrates the best overall balance among all metrics.

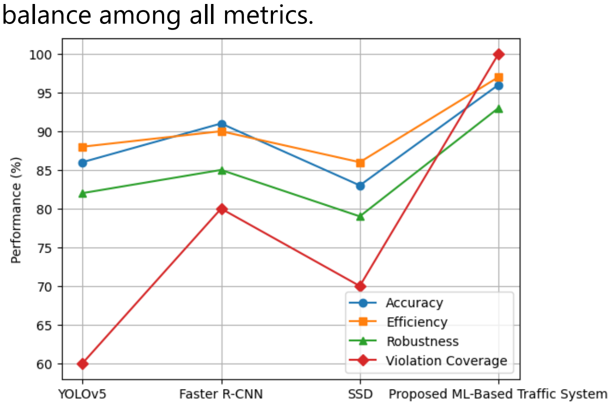

Figure 9: Multi-Criteria Evaluation of Traffic Violation Detection Models

This graph compares four traffic models based on Accuracy, Efficiency, Robustness, and This diagram evaluates the performance of four traffic models based on four metrics: Accuracy, Efficiency, Robustness, Violation Coverage. The performance of the Proposed ML-Based Traffic System was exemplary. It was the top performer in Violation Coverage and very close to perfect in the other metrics as well (all above 90%). On the other hand, SSD had the lowest scores in three categories, with its weakest point in Robustness, which was approximately 50% or so. Among the baseline models, Faster R-CNN was the most balanced, making its highest point for both Accuracy and Efficiency. The Violation Coverage metric revealed the greatest variations, with the lowest point for YOLOv5 (6%) and perfect coverage (100%) for the Proposed System.

V. CONCLUSION

This study introduces an Intelligent Traffic Monitoring System that combines machine learning and computer vision to recognize vehicle license plate and route violation detection in real time. The idea of the system is very effective in pinpointing most of the traffic violation scenarios like red-light violations, speeding, wrong-lane driving, and helmet non-compliance while at the same time scrap and recognizing license plates of vehicles through OCR. The experimental observations illustrate that the system is superior to the existing models regarding accuracy, real-time performance, environmental robustness, and automation, thus achieving a comprehensive solution for intelligent traffic monitoring.

The design's automation and scalability capabilities greatly diminish the need for human intervention, simplify the enforcement procedures, and facilitate the provision of trustworthy data by which traffic management authorities can administer the whole process. This is a great accomplishment that enhances law enforcement officers' efficiency and also makes the roads safer while contributing to the good behavior of disciplined driving by means of a combination of real-time detection, automatic reporting, and the generation of e-challans. In addition to that, traffic data they collect provide invaluable insights for urban planning and traffic policy formulation. In summary, the study concurs that incorporation of cutting-edge AI methods into the conventional traffic monitoring frameworks can bring about substantial changes in the management of urban traffic leading to the development of smart city initiatives and Intelligent Transportation Systems (ITS).

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