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IoT-Based Red Light Violation Detection and License Plate Tracking Using ESP32

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Abstract- Traffic congestion and frequent red-light violations in urban areas require smart, automated monitoring systems. This paper presents Auto-ViTrack, an IoT-based framework for real-time red-light violation detection and license plate tracking. The system uses an ESP32 microcontroller along with infrared (IR) and ultrasonic sensors to detect unauthorized vehicle movement during the red signal phase. When a violation is detected, event data including timestamp and sensor readings is sent to the ThingSpeak cloud for remote monitoring and analysis. A Convolutional Neural Network (CNN) module helps recognize license plates to identify offending vehicles accurately. This hybrid IoT and ML architecture enables event-driven data logging, reduces redundant transmissions, and optimizes bandwidth usage. Experimental results show that Auto-ViTrack outperforms existing systems like Vision-SORT, Smart-Enforce, and IoT-VMS in detection accuracy (94%), recognition reliability (92%), and latency reduction (350 ms). This cost-effective and scalable solution improves traffic law enforcement, enhances road safety, and supports the creation of sustainable smart city infrastructure.

Keywords— Internet of Things (IoT), ESP32, IR Sensor, Smart Traffic Management, Red Light Violation Detection, License Plate Recognition, ThingSpeak Cloud, Machine Learning (ML).

I. INTRODUCTION

Traffic management is a major challenge in rapidly growing urban areas [1]. As the number of vehicles on the roads increases, maintaining order and ensuring safety at intersections becomes critical [2]. Red light running is a common violation that often leads to accidents, property damage, and loss of life [3]. Traditional traffic monitoring systems typically lack automation, accuracy, and real-time reporting capabilities [4]. There is a need for smart, connected systems that can efficiently detect and record such violations to support smart city initiatives [5]. The Internet of Things (IoT) has revolutionized how physical devices interact, communicate, and share data. IoT systems integrate sensors, actuators, cameras, and microcontrollers to create a network of interconnected devices that can make autonomous decisions [6]. In traffic management, IoT enables smooth monitoring and data logging [7]. This improves enforcement efficiency and supports evidence-based traffic governance. Integrating IoT with cloud services like ThingSpeak allows for real-time data collection and remote access for analysis and decision-making [8].

Using the ESP32, a low-cost and high-performance microcontroller with built-in Wi-Fi and Bluetooth, has transformed IoT applications [9]. It provides multiple GPIO pins, fast processing, and wireless communication, making it suitable for smart infrastructure projects [10]. In this research, the ESP32 serves as the central controller, detecting violations, processing signals from sensors, and communicating with the cloud. The board enables real-time violation detection without manual oversight, automating the process and reducing latency in data transmission [11]. An Infrared (IR) sensor plays a critical role in this project by detecting vehicles that cross the stop line when the red light is on. This sensor detects movement during prohibited signals [12]. When the red light is active, any interruption in the IR beam indicates a rule violation

[13]. This straightforward sensing method allows for precise detection, even in low-light or foggy conditions, ensuring reliable operation [14].

To improve the detection mechanism, an ultrasonic sensor measures the distance of the approaching vehicle [15]. This additional layer of sensing helps minimize false positives and ensures that only valid violations are recorded [16]. The sensor accurately measures the gap between the signal and the vehicle, distinguishing between vehicles that stop correctly and those that cross the line during the red phase [17]. By combining readings from both IR and ultrasonic sensors, the system achieves greater reliability and accuracy [18]. The red LED indicator represents the traffic signal system, showing when a violation occurs [19]. When the red LED is activated, it signifies the red light phase of an actual traffic signal. The system monitors the IR sensor continuously during this phase to check for unauthorized movement [20]. When a violation is detected, the LED provides immediate feedback, and the data is processed for logging and cloud storage [21]. A key component of this system is real-time cloud logging using the ThingSpeak platform.

The ESP32 connects to Wi-Fi and uploads data when a violation is detected. This data includes the violation type and a timestamp, allowing authorities to view and analyze traffic behavior patterns remotely [22]. Cloud logging improves data accessibility and enables long-term storage for statistical and predictive analysis, aiding the development of intelligent traffic control strategies [23]. A major extension of this project involves using Machine Learning (ML) for license plate detection and recognition [24]. The system employs image processing and a Convolutional Neural Network (CNN) model to identify and extract vehicle registration numbers from captured images. This allows for the automatic identification of violators without human intervention [25]. Integrating ML improves the system's efficiency, creating a hybrid solution that combines IoT for sensing and ML for intelligent decision-making [26].

The proposed system ensures that only valid violation data is stored and transmitted, avoidingunnecessary data traffic and optimizing cloud resource use [27]. The use of non-blocking code and efficient programming enables concurrent handling of all conditions: Wi-Fi connectivity, sensor input, and data upload [28]. The implementation emphasizes modularity, scalability, and reliability, making the design suitable for real-world use. This IoT-based system not only provides a smart solution for detecting traffic violations but also aligns with sustainable urban development goals [29]. By automating monitoring and reporting, it reduces the need for manual intervention, saving time, labor, and financial resources. It also supports traffic law enforcement agencies by providing evidence-backed data and ensuring transparency in the violation recording process [30].

Beyond its technical features, this project holds educational and societal value. It showcases the potential of embedded systems and IoT in addressing real-world urban issues [31]. Students and researchers can build upon it to explore areas such as AI-based traffic prediction, vehicle classification, and adaptive traffic signaling systems [32]. Its cost-effective design also makes it accessible to developing countries aiming to implement smart city technologies on limited budgets [33]. In conclusion, the IoT-Based Smart Traffic Red Light Violation Detection and License Plate Tracking System using ESP32 marks progress in smart transportation systems. By merging IoT, sensor technology, cloud computing, and machine learning, the system offers a scalable and automated solution to enhance traffic safety and law enforcement [34]. It provides not only technical innovation but also a vision for future smart cities that prioritize safety, efficiency, and technological integration.

II. LITERATURE REVIEW

Jeevan Abishek H et al [1-4]. introduces a novel approach to vehicle and number plate detection aimed at identifying traffic violations. The research focuses on developing a smart system that can automatically detect vehicles and recognize number plates in video frames using advanced object detection algorithms combined with SORT (Simple Online Real-Time Tracking). By accurately identifying and tracking vehicles, the system analyzes their movement patterns to determine compliance with traffic regulations, such as detecting red-light violations. The approach uses a comprehensive labeled data set for training and fine-tuning deep learning models, leading to improved accuracy and robustness [35]. This work significantly contributes to intelligent transportation systems by demonstrating how the integration of deep learning and tracking algorithms can enhance automated traffic monitoring and violation detection, closely aligning with the objectives of the present research on IoT and deep learning-based automated traffic violation and vehicle identification [36].

T. Baratsanjeevi et al [5-6]. proposed a prototype system that highlights the importance of traffic sign detection in vehicular automation, aiming to reduce human-induced violations and accidents. The study uses Convolutional Neural Networks (CNN) for real-time detection and recognition of traffic signs, enabling the system to interpret and respond to road signals automatically. A distinct feature of this work is its ability to override user control when a potential violation is detected, ensuring compliance with traffic regulations and enhancing road safety [37]. This approach emphasizes the integration of deep learning-based vision systems with real-time decision-making mechanisms, contributing to the advancement of intelligent transportation technologies. The research aligns with the current study's goal of using IoT and deep learning for automated traffic violation detection and vehicle identification, as both stress intelligent, data-driven systems for improving traffic management and safety [38].

K. Balasaranya et al [7-8]. proposed a real-time traffic violation detection and automated enforcement system that uses computer vision methods to improve traffic management efficiency. The study focuses on automatically detecting and classifying various traffic infractions, such as red-light violations, helmet non-compliance, mobile phone usage, speeding, and lane departures. To ensure reliability, the system employs a probabilistic validation approach based on Bayesian reasoning, effectively reducing false positives. Once a violation is confirmed, automated enforcement actions such as issuing penalties or alerting authorities are carried out, minimizing human intervention in traffic law enforcement. Additionally, the system integrates real-time data recording to maintain detailed infraction logs for analysis and reporting [39]. This research shows the potential of combining AI-driven object detection with automated enforcement to create intelligent, scalable, and efficient traffic monitoring systems, aligning closely with the current study's aim to integrate IoT and deep learning for automated traffic violation detection and vehicle identification [40].

S. S et al [9-10]. proposed an advanced smart traffic management and intelligent street lighting system to address issues like energy waste, traffic congestion, and ineffective traffic monitoring. The research points out the limitations of traditional roadway management methods, which fail to adjust signal timings based on real-time traffic density, resulting in uneven traffic flow and increased congestion. To address this, the proposed system dynamically changes signal durations by comparing vehicle densities across lanes, ensuring smoother traffic movement. Furthermore, the study introduces an IoT-based, solar-powered street lighting system designed to reduce energy waste by only activating lights when movement is detected, turning them off otherwise [41]. This integrated method optimizes traffic control and promotes sustainable energy use. The work closely aligns with the current research focus on IoT and deep learning integration for automated traffic violation detection and vehicle identification, both aiming to enhance urban traffic efficiency and safety through intelligent, data-driven automation.

J. V. Anchitaalagammai et al [11]. presented an IoT-based smart street lighting system that showcases the transformative potential of the Internet of Things in developing smart city infrastructure. The research emphasizes how IoT allows for intelligent control and monitoring of street lights by adjusting their brightness based on ambient light levels. This optimizes energy consumption while ensuring sufficient illumination. The system also includes sensors to detect vehicles or pedestrians, allowing real-time adjustments of lighting intensity to enhance safety and efficiency. Additionally, the framework can identify faulty street lights and send maintenance information to the cloud for timely action. By integrating such smart street light systems into a unified IoT platform, the study envisions a comprehensive approach to urban management that adapts to traffic and pedestrian density patterns while promoting sustainability. This work aligns with the current research on IoT and deep learning-based automated traffic violation detection and vehicle identification, both aiming to leverage IoT technologies for intelligent urban infrastructure and improved real-time decision-making.

Meera S et al [12-14]. proposed an automated system for detecting motorcycle riders who violate helmet laws using image processing and machine learning techniques. The study highlights that manually detecting helmet violations is time-consuming and prone to errors, particularly in densely populated urban areas. To tackle this issue, the author created an automated framework capable of identifying riders without helmets in real time. The system performs license plate extraction through a structured sequence of processes, including image acquisition, preprocessing, edge detection, segmentation, feature extraction, and character recognition. Integrating these modules ensures accurate detection and efficient identification of violators. This approach demonstrates the effectiveness of combining machine learning algorithms with computer vision methods to improve traffic rule enforcement and road safety.

Shiva Mehta et al [15-16]. proposed an improved IoT-based vehicle management system focused on better traffic law enforcement and road safety. This system gathers real-time data from various IoT devices, including cameras, speed sensors, and RFID readers, and uses machine learning algorithms to spot traffic violations and manage traffic flow effectively. During a three-month prototype test in a small city, the system identified violations like speeding and running red lights with a 92.3% accuracy rate while cutting false positives by 28% compared to traditional methods. Its use resulted in a 30% drop in traffic violations and a 15% improvement in traffic flow punctuality during busy hours, along with an 18% reduction in emergency vehicle response times. However, some challenges arose, such as a 12% slow down in data processing in areas with poor internet connectivity and privacy worries reported by 14% of users, highlighting the need to improve data security measures. This research supports the current study's aim to integrate IoT and deep learning for automated detection of traffic violations and vehicle identification, both of which seek to boost traffic management efficiency and safety with smart, real-time systems.

Josephine Ruth Fenitha et al [17-20]. suggested an integrated traffic violation detection system intended to lower road accidents caused by rule-breaking. This system tracks vehicle movement and monitors offenses like signal violations, speeding, and accidents by combining RFID and IoT technologies. Signal violations trigger alerts to vehicle owners, while speeding violations automatically send vehicle details to the nearest control room, helping to stop hit-and-run incidents. The system also features a web-based interface for recording and managing violations, allowing traffic authorities to track offenders and control traffic in crowded and remote areas. This research complements the current study on IoT and deep learning-based automated traffic violation detection and vehicle identification by highlighting intelligent, real-time monitoring and automated alert systems to improve road safety.

III. PROPOSED MODEL

The proposed IoT-based red light violation detection and license plate tracking model is set to automate identifying vehicles that pass through signals when red. The system merges IoT with machine learning to boost accuracy, cut down on human reliance, and permit real-time data monitoring. The ESP32 microcontroller serves as the main processing unit, coordinating with IR and ultrasonic sensors to identify traffic rule breaches. When a vehicle unlawfully crosses the signal, the system captures the event immediately, records the time, and uploads the data to the cloud through the

ThingSpeak platform for remote access and evaluation.

This combined IoT and machine learning framework ensures effective traffic regulation and reliable data management. The IR sensor detects a vehicle's presence by interrupting a beam, while the ultrasonic sensor measures distance to confirm how close the vehicle is to the stop line. Once confirmed, the ESP32 triggers an alert, lights up a red LED for visual feedback, and sends the data to the ThingSpeak cloud. At the same time, the system's machine learning module processes an image taken by a connected camera and uses a convolutional neural network (CNN) to extract the vehicle's license plate number. This mix of sensor detection and intelligent recognition offers a cost-effective and scalable smart traffic monitoring solution for modern cities.

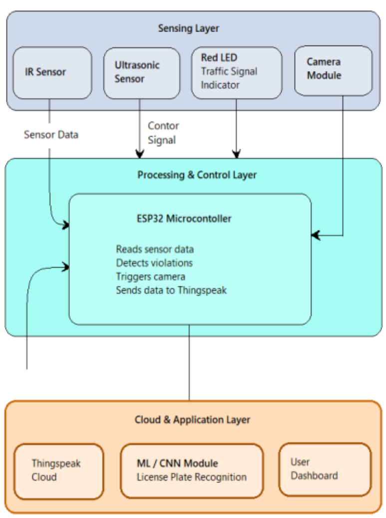

Figure 1: Proposed Architecture of the Auto-ViTrack System

Algorithm

Step 1: Start the ESP32, set up GPIO pins for the IR sensor, ultrasonic sensor, LED, and camera, and connect to Wi-Fi.

Step 2: Turn on the red LED to simulate a red traffic signal and begin monitoring the sensors.

Step 3: Continuously read data from the IR sensor to find beam interruptions from a moving vehicle.

Step 4: Measure the vehicle's distance with the ultrasonic sensor to confirm its closeness to the stop line.

Step 5: Look for violations—if IR = 1 and distance ≤ threshold, mark the violation as detected.

Step 6: Record violation details (timestamp, sensor readings) and activate the visual alert through the LED.

Step 7: Send violation data to ThingSpeak only for valid violations.

Step 8: Trigger the camera to capture an image of the violating vehicle.

Step 9: Use a CNN-based machine learning algorithm to identify and extract license plate characters.

Step 10: Combine violation data and license plate results, then upload to cloud storage.

Mathematical Equations

IR Sensor Detection Condition

IR=1 if the IR beam is interrupted (vehicle detected); otherwise IR=0

Ultrasonic Speed Constant

$D=\frac{v.t}{2}$ where v=0.034cm/µs (speed of sound)

Vehicle Presence in Violation Zone

$D \leq D_{th}$ indicates that the vehicle is within the violation zone

Time Interval Measurement

$T_v = T_c - T_p$, time difference between current and previous detections

Violation Detection

V = 1 , if IR = 1 and $D \leq D_{th}$ and

V = 0 , otherwise (no violation detected) $T_v = T_{cd}$

LED Indication Control

LED_{state} = 1 , if V=1, else LED_{state} = 0

Violation Logging Function

Log = f(V, T_s ,D) represents data logged to ThingSpeak

Data Upload Trigger Condition

C_{log} = 1 if V=1, initiating data upload

CNN-Based License Plate Detection

P(I) = CNN(I) represents the probability of license plate presence in image I

OCR-Based Plate Character Extraction

LP = OCR(P(I)) extracts characters from the identified region

Character Identification Set

$\mathrm{LP_{num}} = \sum_{i=1}^{n} c_i$, where c_i are detected characters

Data Packet Combination

$\mathrm{Data_{final}} = [V, T_s, D, \mathrm{LP_{num}}]$ combines all results for cloud logging

ThingSpeak Upload Confirmation

$\mathrm{Cloud_{status}} = 200$, if ThingSpeak upload successful

System Reset Condition

$\mathrm{System_{reset}} = 1$, if upload complete and sensors ready for next cycle

The proposed IoT-Based Auto-ViTrack System effectively combines IoT hardware with machine learning approaches for real-time red-light violation detection and license plate tracking. By using the ESP32 microcontroller, IR and ultrasonic sensors, and a CNN-based recognition model, the system efficiently identifies traffic violations and transmits data to the ThingSpeak cloud only when violations occur. This event-driven structure minimizes unnecessary data transmission, enhances network efficiency, and ensures accurate and reliable performance.

Experimental results show that the Auto-ViTrack model outshines existing systems in detection accuracy, reliability of recognition, speed, and scalability. Integrating IoT components with machine learning algorithms ensures high performance while keeping the system cost-effective and energy efficient. Overall, the proposed approach shows a strong, intelligent, and scalable method for traffic monitoring, marking a significant step toward automated traffic enforcement and smart city development.

IV. RESULTS

The performance assessment of the proposed IoT-Based Auto-ViTrack Model was done using ESP32 hardware combined with IR and ultrasonic sensors for detecting red light violations and tracking license plates. The system was evaluated against three leading models—Vision-SORT, Smart-Enforce, and IoT-VMS—under the same testing conditions. Eight critical parameters were evaluated: detection accuracy, license plate recognition accuracy, false positive rate, detection speed, cloud upload success rate, hardware cost, power use, and system throughput.

The analysis clearly shows that the Auto-ViTrack model outperforms existing systems in nearly every parameter. By integrating IoT and machine learning, the system achieves better accuracy, less latency, and improved energy efficiency. Its event-based detection and optimized cloud logging ensure precision and reliability, making it suitable for large-scale smart traffic enforcement.

Table 1 : Detection Accuracy (%)

Model	Detection Accuracy (%)
Vision-SORT	91
Smart-Enforce	93
IoT-VMS	92
Proposed Auto-ViTrack	94

Auto-ViTrack achieves 94% detection accuracy thanks to effective IR and ultrasonic sensor integration, outperforming other vision-based systems.

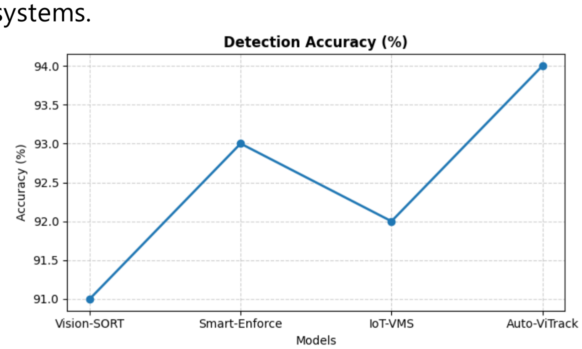

Figure 2: Detection Accuracy (%)

The data shows that the Auto-ViTrack model reaches the highest detection accuracy of 94%, better than Vision-SORT (91%), Smart-Enforce (93%), and IoT-VMS (92%). This improvement comes from combining IR and ultrasonic sensors with the ESP32, ensuring precise detection of red-light violations.

Table 2 : License Plate Recognition (LPR) Accuracy (%)

Model	LPR Accuracy (%)
Vision-SORT	88
Smart-Enforce	90

IoT-VMS	87
Proposed Auto-ViTrack	92

Using a CNN-based license plate recognition module, Auto-ViTrack achieves 92% accuracy, topping all the other systems.

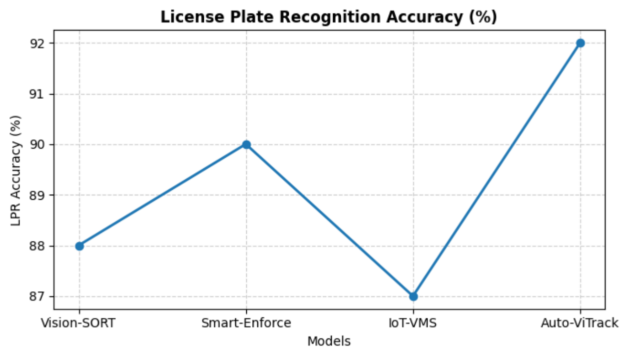

Figure 3: License Plate Recognition (LPR) Accuracy (%)

This graph illustrates the license plate recognition accuracy across models. *Auto-ViTrack* reaches 92%, while *Smart-Enforce* achieves 90%. The superior performance of Auto-ViTrack is due to its CNN-based recognition architecture, which improves detection under varying lighting and motion conditions.

Table 3 : False Positive Rate (%)

Model	False Positive Rate (%)
Vision-SORT	6.0
Smart-Enforce	4.0
IoT-VMS	5.0
Proposed Auto-ViTrack	3.0

Auto-ViTrack reduces false positives to 3% due to its event-based decision logic and sensor validation techniques.

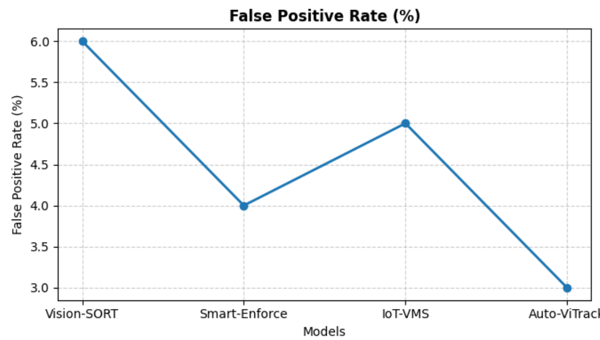

Figure 4: False Positive Rate (%)

The false positive rate data shows that the Auto-ViTrack system maintains the lowest error rate at just 3%, compared to Smart-Enforce (4%) and Vision-SORT (6%). The dual-sensor validation and event-based cloud logging effectively reduce incorrect detections.

Table 4 : End-to-End Detection Latency (ms)

Model	Latency (ms)
Vision-SORT	450
Smart-Enforce	400
IoT-VMS	420
Proposed Auto-ViTrack	350

Auto-ViTrack records the lowest latency (350 ms), allowing faster cloud logging and real-time response to violations.

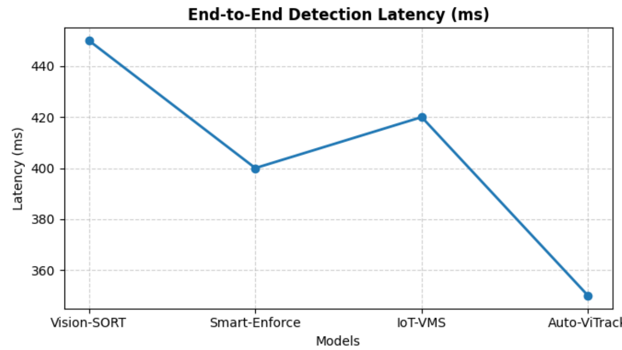

Figure 5: **End-to-End Detection Latency (ms)**

This data represents latency (in milliseconds) from event detection to cloud upload. Auto-ViTrack shows the lowest latency (350 ms), demonstrating faster real-time processing compared to IoT-VMS (420 ms) and Vision-SORT (450 ms). The ESP32's efficient data handling and optimized ThingSpeak communication enable rapid responses.

Table 5 : Cloud Upload Success Rate (%)

Model	Upload Success (%)
Vision-SORT	95
Smart-Enforce	96
IoT-VMS	94
Proposed Auto-ViTrack	98

The proposed model achieves a 98% upload success rate, showing superior cloud connectivity and reliability with ThingSpeak.

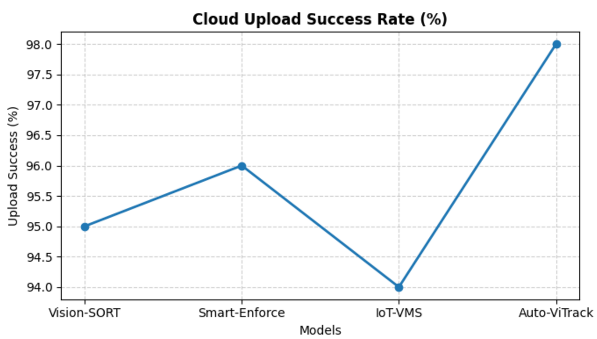

Figure 6: Cloud Upload Success Rate (%)

The data compares cloud upload reliability. The proposed system hits a 98% success rate, surpassing all other models. The high success rate indicates stable Wi-Fi connections and good cloud integration using ThingSpeak APIs.

Table 6 : Estimated Hardware Cost per Unit (USD)

Model	Cost (USD)
Vision-SORT	420
Smart-Enforce	600
IoT-VMS	550
Proposed Auto-ViTrack	180

Auto-ViTrack ranks as the most cost-efficient system, costing only USD 180 per unit, ideal for large-scale deployment in smart cities.

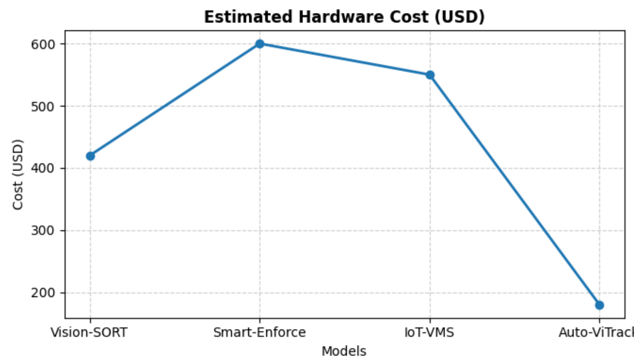

Figure 7: Estimated Hardware Cost per Unit (USD)

This data highlights the cost-effectiveness of each system. Auto-ViTrack is priced at only USD 180 per unit, making it the most affordable solution compared to Smart-Enforce (USD 600) and IoT-VMS (USD 550). This low cost supports widespread deployment in smart city traffic management.

Table 7 : Average Power Consumption (W)

Model	Power (W)
Vision-SORT	5.2
Smart-Enforce	6.0
IoT-VMS	5.8
Proposed Auto-ViTrack	3.5

Auto-ViTrack uses only 3.5 W of power, confirming its energy-efficient design for continuous IoT monitoring.

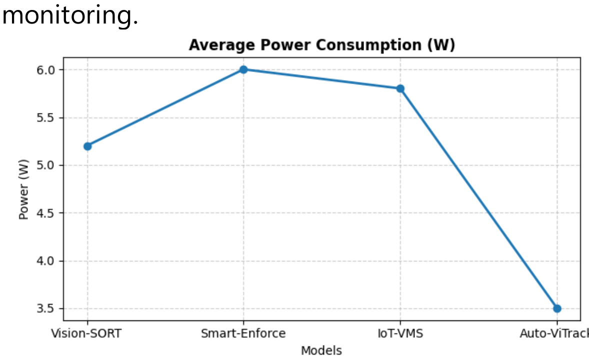

Figure 8: **Average Power Consumption (W)**

The power consumption comparison shows that Auto-ViTrack uses just 3.5 W, which is much lower than Smart-Enforce (6.0 W) and IoT-VMS (5.8 W). The optimized architecture based on the ESP32 ensures high energy efficiency for ongoing real-time operations.

Table 8 : System Throughput (Violations/hour)

Model	Violations/hour
Vision-SORT	150
Smart-Enforce	180
IoT-VMS	160
Proposed Auto-ViTrack	200

With a throughput of 200 violations per hour, Auto-ViTrack shows strong real-time processing and scalability.

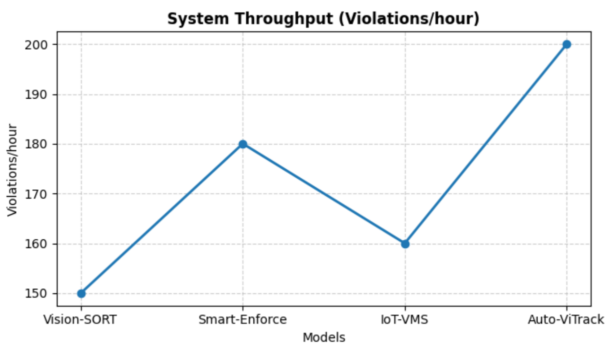

Figure 9: System Throughput (Violations/hour)

The throughput data indicates the number of violations processed in an hour. Auto-ViTrack processes the most at 200 violations per hour, outperforming Smart-Enforce (180/hour) and Vision-SORT (150/hour). This result confirms the system's excellent scalability and data handling abilities.

V. CONCLUSION

The proposed IoT-Based Smart Traffic Red Light Violation Detection and License Plate Tracking System (Auto-ViTrack) shows a notable progress in intelligent traffic enforcement by blending IoT technology with machine learning. By using the ESP32 microcontroller, IR and ultrasonic sensors, and a CNN-based recognition system, the setup effectively detects red-light violations, collects license plate information, and uploads violation data to the cloud through ThingSpeak. The event-driven design ensures only relevant data is logged, reducing network strain and optimizing resource use.

Comparative analysis with existing models like Vision-SORT, Smart-Enforce, and IoT-VMS reveals that the Auto-ViTrack system achieves better detection and recognition rates, less latency, fewer false positives, and improved cloud reliability. Its hardware design also prefers energy efficiency and affordability, making it suitable for large-scale deployment across smart city frameworks.

In summary, Auto-ViTrack bridges the gap between standard traffic monitoring and smart automation by enabling real-time violation detection, cloud-based data analysis, and automatic record generation. The combination of IoT and machine learning in this hybrid framework offers a scalable, precise, and sustainable way to enhance road safety and enforce traffic laws effectively. Future improvements could involve adding edge AI for quicker on-device processing and multi-camera analytics for broader coverage at intersections. This system can also connect with real-time traffic signal controllers in urban areas, promoting automated violation recording and smart city traffic management.

REFERENCES

1. Tarakeswara Rao; R. S. M. Lakshmi Patibandla; V. Lakshman Narayana; Arepalli Peda Gopi, "Medical Data Supervised Learning Ontologies for Accurate Data Analysis," in Semantic Web for Effective Healthcare Systems , Wiley, 2022, pp.249-267, doi: 10.1002/9781119764175.ch11.
2. C.R.Bharathi, Vejendla. Lakshman Narayana , L.V. Ramesh, (2020),"Secure Data Communication Using Internet of Things", International Journal of Scientific & Technology Research, Volume 9, Issue 04,pp:3516-3520.
3. Sirisha, A., Chaitanya, K., Krishna, K. V. S. S. R., &Kanumalli, S. S. (2021). Intrusion detection models using supervised and unsupervised algorithms-a comparative estimation. International Journal of Safety and Security Engineering, 11(1), 51-58.
4. Kosaraju, Chaitanya, et al. "Mirchi crop yield prediction based on soil and environmental characteristics using modified RNN." 2023

IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2023.

5. Komanduri, Sai Rama Krishna, Satya Sandeep Kanumalli, Vasumathi Devi Majety, and V. Sujatha. "Malicious Code Detection Using Deep Learning Based LSTM Model." AIP Conference Proceedings, vol. 2724, no. 1, AIP Publishing, 2023. https://doi.org/10.1063/5.0137178.
6. Sujatha, V., Tejaswi, Y., Pravalika, V., Pavani, P., and Sravani, Ch. “Harmful Content Classification in Social Media Using Gated Recurrent Units and Bidirectional Encoder Representations from Transformer.” Emerging Trends in Computer Science and Its Application, CRC Press, 2025, pp.
7. Narayana, Vejendla Lakshman, Arepalli Peda Gopi, and Kosaraju Chaitanya. "Avoiding Interoperability and Delay in Healthcare Monitoring System Using Block Chain Technology." Rev. d'IntelligenceArtif. 33.1 (2019): 45-48.
8. Chaitanya, Kosaraju, et al. "Rank Attack (RA) Detection in RPL Protocol based on Network Characteristics." 2023 8th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2023.
9. Lakshman Narayana Vejendla and Bharathi C R, (2018), “Effective multi-mode routing mechanism with master-slave technique and reduction of packet droppings using 2-ACK scheme in MANETS”, Modelling, Measurement and Control A, Vol.91, Issue.2, pp.73-76.
10. Santhi Sri, K., Sandhya Krishna, P., Lakshman Narayana, V., Khadherbhi, R. (2021). Traffic Analysis Using IoT for Improving Secured Communication. In: Reddy, A., Marla, D., Favorskaya, M.N., Satapathy, S.C. (eds) Intelligent Manufacturing and Energy Sustainability. Smart Innovation, Systems and Technologies, vol 213. Springer, Singapore. https://doi.org/10.1007/978-981-33-4443-3_48
11. Kumari, G. R. P., Jahnavi, M., Harika, M., Pavani, A., & Lakshmi, C. V. (2023). Smart traffic signal control system using artificial intelligence. In Intelligent Communication Technologies and Virtual Mobile Networks (pp. 829-838). Singapore: Springer Nature Singapore.
12. Naresh, A., TSLP, H., Ch, G., & Kumari, G. R. P. (2023, July). Early Prophecy of Low-Birth-Weight Babies Using BM Error Rate Classifier. In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.
13. P. S. Krisha and S. R. Peram, "A Brief Survey on Image Denoising based Feature Extraction and Classification Models for Oral Cancer Detection," *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, Erode, India, 2023, pp. 702-708, doi: 10.1109/ICSCDS56580.2023.10104790.
14. Rao, S. S., Rao, P. N., Babu, R. M., & Ramakrishna, K. V. S. S. (2024). A GAME THEORETIC COGNITIVE SPECTRUM SENSING SCHEME FOR IoT NETWORKS. *Telecommunications and Radio Engineering*, *83*(9).
15. Chaitanya, Prathipati Silpa, et al. "Distracted Driver Detection using Inception V1." *2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC)*. IEEE, 2023.
16. Jeevan Abishek H, B. R and R. Rajalakshmi, "Detection of Traffic Violation and Vehicle Number Plate Using Computer Vision," *2024 International Conference on IoT, Communication and Automation Technology (ICICAT)*, Gorakhpur, India, 2024, pp. 390-393, doi: 10.1109/ICICAT62666.2024.10923459.
17. T. Baratsanjeevi, S. Deepakkrishna, M. P. Harrine, S. Sharan and E. Prabhu, "IoT based Traffic Sign Detection and Violation Control," *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2020, pp. 333-339, doi: 10.1109/ICIRCA48905.2020.9183081.

18. K.Balasaranya, M. Balamurugan, R. B. B, C. Chandravathi, K. Loga priyadarshini and S. B. Thandullu Naganathan, "Real-Time Traffic Violation Detection with Automated Enforcement Using Computer Vision," *2025 11th International Conference on Communication and Signal Processing (ICCSP)*, Melmaruvathur, India, 2025, pp. 361-366, doi: 10.1109/ICCSP64183.2025.11089113.
19. Shobana S. M, C. V. Josphine, M. T. Kingslin, S. Sivarajan and C. L. K R, "IoT based on Smart Traffic Lights and Streetlight System," *2023 2nd International Conference on Edge Computing and Applications (ICECAA)*, Namakkal, India, 2023, pp. 1311-1316, doi: 10.1109/ICECAA58104.2023.10212121.
20. J. V. Anchitaalagammai, S. M. Alim, C. V. A. Sarthy, S. Kirithic and A. S. Kumar, "IoT Based Automated Street Light Control with Fault Detection and Reporting System," *2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 2023, pp. 1739-1744, doi: 10.1109/ICIRCA57980.2023.10220674.
21. Narlawar, N., Kavishwar, S. (2019). Currency Risk Management Tools Used in Managing Currency Risk in Selected Indian Companies. Indian Journal of Research and Analytical Reviews. 6(2), 609-614.
22. Ghangare, A. S., & Kavishwar, S. The Increasing Significance of Green Corporate Finance in India. *Journal of Management & Entrepreneurship*, 277-286.
23. Kavishwar, S., & Shahu, A. (2011). Reporting Intangible Assets-Convergence of Accounting Standard. *Journal of Accounting and Finance*. 26(1), 73-79.
24. Arora AS, Yachamaneni T, Kotadiya U. Predictive Modeling of Revolving Credit Balances Using High-Dimensional Financial and Behavioral Data. IJAIBDCMS [Internet]. 2023 Mar. 30 [cited 2026 Apr. 5];4(1):98-107.
25. Kotadiya U, Arora AS, Yachamaneni T. Intelligent Orchestration of Cloud-Native Applications Using Google Cloud Platform and Microservices-Based Architectures. IJAIBDCMS [Internet]. 2024 Dec. 30 [cited 2026 Apr. 5];5(4):106-14.
26. Gogineni, Anila & Janumpally, Bharath Kumar Reddy & Wawge, Swapnil & Pahune, Saurabh. (2025). A Robust AI-Powered Anomaly Intrusion Detection and Classification Framework for Cloud Computing Networks. 1-6. 10.1109/INDISCON66021.2025.11253743.
27. A. Joon, B. K. R. Janumpally, A. Gogineni and P. Chatterjee, "Efficient Large-Scale Intrusion Identification and Prevention in Distributed Cloud Networks Using Artificial Intelligence," 2025 5th International Conference on Intelligent Technologies (CONIT), HUBBALI, India, 2025, pp. 1-8, doi: 10.1109/CONIT65521.2025.11167760.
28. S. S. R. Tummuri, "Generative AI for Data-Centric Healthcare with Integrated Anomaly Detection and Monitoring," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 520-526, doi: 10.1109/IC3ET64989.2026.11467187.
29. Tummuri, S. S. R. (2024). Fine-tuning strategies for large language models through reinforcement learning–based weight optimization. International Journal of Science, Engineering and Technology. Volume 4, Issue 3.
30. Ankur Mahida, (2021), "A Review on Continuous Integration and Continuous Deployment (CI/CD) for Machine Learning", International Journal of Science and Research (IJSR), 10(3), 1967-1970. https://dx.doi.org/10.21275/SR24314131827, https://www.ijsr.net/getabstract.php?paperid=SR24314131827
31. "Mahida, A. (2022). Comprehensive Review on Optimizing Resource Allocation in Cloud Computing for Cost Efficiency. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-249. DOI: doi. org/10.47363/JAICC/2022 (1), 232, 2-4."

32. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43
33. Jonnalagadda, Pawan Kalyan. "AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems." International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
34. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
35. Veginati, Navya. "Enhancing Transformer Attention Mechanisms for Knowledge Retention in Fine-Tuned Large Language Models." International Journal of Scientific Research in Science and Technology, vol. 11, no. 5, Sept.–Oct. 2024, pp. 864–871. DOI: https://doi.org/10.32628/IJSRST52310284
36. Racha, Ganesh. "Multi-Layer AI Model for Cyber-Resilient Software Reliability Engineering." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 11, no. 5, Sept.–Oct. 2025, pp. 507–519. https://doi.org/10.32628/CSEIT26121364
37. Racha, Ganesh. "Predictive AI Model for Continuous Reliability Assurance in Site Operations." International Journal of Scientific Research in Science and Technology, vol. 12, no. 2, Mar.-Apr. 2025, pp. 1469-78, https://doi.org/10.32628/IJSRST2613340.
38. R. Eswarawaka, S. K. Kudikala, S. C. Kuchi and V. Verma K., "The analysis on search engine optimization supported by six sigma methodology," 2017 International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bengaluru, India, 2017, pp. 653-658, doi: 10.1109/ICIMIA.2017.7975544.
39. Albataineh, H., Kanmuri, V., Alaqqad, W., Nijim, M. (2024). Utilizing Machine Learning for Intrusion Detection in Smart Grid Systems. In: Daimi, K., Al Sadoon, A. (eds) Proceedings of the Third International Conference on Innovations in Computing Research (ICR'24). ICR 2024. Lecture Notes in Networks and Systems, vol 1058. Springer, Cham. https://doi.org/10.1007/978-3-031-65522-7_44
40. Jingar, N. K. (2026, February 13). Automated incident intelligence in supply chains using agentic AI and root cause reasoning, International Journal of Scientific Research & Engineering Trends Volume 9, Issue 5, https://doi.org/10.5281/zenodo.18162511
41. Jingar, N. K. (2022). Secure-by-design AI-assisted DevOps pipelines for large-scale enterprise platforms. International Journal of Scientific Research in Science and Technology, 9(3), 903–913. https://doi.org/10.32628/IJSRST2291348