International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

Edge-AI Enabled Multi-Violation Traffic Monitoring System for Smart Cities

Lavanya.P.S. [1]
Student [1]
pslavanya2202@gmail.com [1]
Misrimal Navajee Munoth Jain Engineering College, Chennai, India

Ms.V.K.G.Kalaiselvi [2]
Assistant Professor [2]
vkgkalaiselvi@gmail.com [2] Sri Sairam Engineering College, Chennai, India

Mr. P.Selvakumar [3]
Industry [3]
p.selvakumar1971@gmail.com

Abstract*-Rapid urbanization and the continuous growth in vehicular density have significantly increased the frequency of traffic violations, posing serious challenges to road safety and efficient traffic management in modern smart cities. Conventional monitoring approaches, which rely heavily on manual enforcement and centralized surveillance, often fail to provide scalable and real-time solutions. To address these limitations, this paper proposes a context-aware edge-AI enabled multi-violation traffic monitoring system designed for autonomous and efficient roadside enforcement.The proposed system integrates lightweight deep learning models for real-time vehicle detection and tracking, combined with contextual analysis of traffic signals and lane structures to accurately identify multiple types of violations, including signal jumping, helmet non-compliance, and improper lane usage. Unlike traditional systems that rely solely on detection, the framework introduces a context-driven decision mechanism that evaluates vehicle behavior based on dynamic traffic conditions. Furthermore, a risk prediction module is incorporated to estimate the likelihood of potential violations before they occur, enabling proactive traffic management.The entire pipeline is deployed on edge computing devices, reducing latency and minimizing dependency on cloud infrastructure while ensuring data privacy. A lightweight monitoring dashboard is also developed to visualize violation events, timestamps, and location-based analytics for real-time decision-making. Experimental evaluation demonstrates that the proposed system achieves high detection accuracy with real-time inference performance, making it suitable for practical deployment.The results highlight the effectiveness of combining edge intelligence, contextual awareness, and predictive analytics in building next-generation intelligent transportation systems. This work contributes toward scalable, privacy-preserving, and proactive traffic enforcement solutions for smart city environments.

Keywords— Edge AI, Smart Cities, Traffic Violation Detection, Computer Vision, Context-Aware Systems, Risk Prediction, YOLO, Intelligent Transportation Systems.

I. INTRODUCTION

Rapid urbanization and the continuous growth in vehicle population have significantly increased traffic congestion and violations in modern cities. Traffic rule violations such as red-light jumping, over-speeding, lane indiscipline, and illegal turns are major contributors to road accidents and public safety concerns. Traditional traffic monitoring systems rely heavily on manual enforcement and centralized surveillance, which are often inefficient, resource-intensive, and incapable of scaling to real-time smart city requirements.

With the advancement of computer vision and deep learning, automated traffic monitoring systems have gained significant attention. Recent approaches utilize object detection models and video analytics to identify violations such as signal jumping and speed violations [2], [4]. Additionally, intelligent systems powered by machine learning algorithms have demonstrated the ability to process large-scale traffic data and extract meaningful insights for decision-making [6]. The integration of

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

edge computing has further enabled real-time processing by reducing latency and dependency on cloud infrastructure [1], [8].

Despite these advancements, existing systems exhibit several limitations. Most current solutions focus on detecting individual violations rather than handling multiple violations within a unified framework. Furthermore, these systems operate based on predefined rules without incorporating contextual understanding of traffic environments, such as signal states, vehicle interactions, and road conditions [5]. As a result, they often fail to accurately interpret complex real-world scenarios.

Another major limitation is the lack of proactive capabilities. Current systems are primarily reactive, identifying violations only after they occur, rather than predicting potentially risky behavior in advance [3]. In addition, reliance on cloud-based architectures introduces challenges related to latency, bandwidth usage, and data privacy, which are critical concerns in large-scale smart city deployments.

To address these challenges, this paper proposes an Edge-AI Powered Multi-Violation Traffic Monitoring System for Smart Cities. The proposed system integrates real-time object detection and tracking with context-aware analysis to identify multiple traffic violations simultaneously. Unlike conventional approaches, the system incorporates a behavioral analysis component to understand vehicle movement patterns and a predictive module to estimate potential violations before they occur.

The key contributions of this work include the development of a unified multi-violation detection framework, the incorporation of context-aware decision-making for improved accuracy, and the deployment of the system on edge devices to enable low-latency and privacy-preserving operation. This approach aims to enhance traffic monitoring efficiency and support the development of safer and more intelligent transportation systems.

The remainder of this paper is organized as follows. Section II presents the literature review and analysis of existing methods. Section III describes the proposed system architecture and methodology. Section IV discusses implementation and experimental results. Finally, Section V concludes the paper and outlines future research directions.

II. RELATED WORK

Recent advancements in intelligent transportation systems have led to the development of automated traffic monitoring solutions using computer vision and deep learning techniques. Early approaches primarily focused on detecting individual traffic violations such as red-light jumping or over-speeding using image processing and rule-based methods. For instance, vision-based traffic signal violation detection systems utilize video feeds to identify vehicles crossing stop lines during red signals [2], [6]. While these methods demonstrate reasonable accuracy, they are often limited to single-task detection and lack adaptability to dynamic traffic environments.

To improve scalability and efficiency, several studies have proposed integrated systems capable of detecting multiple violations. Intelligent traffic monitoring frameworks have been developed to identify violations such as over-speeding, signal jumping, and lane indiscipline within a unified system [4], [5]. These approaches leverage deep learning models for object detection and classification, enabling automated monitoring without continuous human intervention. However, most of these systems operate using predefined thresholds and rules, which restrict their ability to interpret complex real-world scenarios.

With the rapid growth of smart cities, edge computing has emerged as a promising solution for real-time traffic monitoring. Edge-AI-based systems process data closer to the source, thereby reducing latency and minimizing dependence on centralized cloud infrastructure. Studies have demonstrated the effectiveness of deploying lightweight deep learning models on edge devices for tasks such as pedestrian detection and traffic analysis [1], [8]. These systems offer faster response times and improved data privacy, making them suitable for large-scale urban deployments. Nevertheless, many existing edge-based solutions focus primarily on detection tasks without incorporating higher-level behavioral analysis.

In addition to detection, recent research has explored the use of deep learning for traffic

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

accident detection and predictive analytics. Models trained on large-scale datasets can identify abnormal patterns and detect incidents in real time [9], [10]. Although these approaches highlight the potential of predictive intelligence in traffic systems, they are typically designed for post-event analysis rather than proactive violation prevention.

Object detection and tracking algorithms form the backbone of modern traffic monitoring systems. Frameworks such as YOLO have been widely adopted due to their real-time performance and high detection accuracy [13], [14], [15]. Similarly, tracking algorithms like DeepSORT enable consistent vehicle tracking across video frames, supporting behavior analysis and trajectory estimation [16]. Benchmark datasets such as Pascal VOC and MS COCO have played a crucial role in training and evaluating these models [17], [18]. Despite their effectiveness, these techniques are generally used as standalone components and are not fully integrated into context-aware decision-making systems.

Furthermore, recent studies have emphasized the importance of contextual understanding in traffic analysis. Context-aware frameworks attempt to incorporate environmental factors such as road structure, traffic signals, and vehicle interactions to improve detection accuracy [11], [12]. While these approaches show promising results, they often lack integration with real-time edge deployment and multi-violation detection capabilities.

In summary, although significant progress has been made in traffic violation detection using deep learning and edge computing, existing systems still face several limitations. Most approaches focus on isolated detection tasks, lack contextual awareness, and do not provide proactive risk prediction. These gaps highlight the need for a unified, context-aware, and edge-enabled system capable of detecting and predicting multiple traffic violations in real time.

III. RESEARCH GAP

Despite significant advancements in traffic monitoring systems using computer vision, deep learning, and edge computing, several critical gaps remain in existing research. These limitations restrict the effectiveness of current systems in real-world smart city environments.

Firstly, most existing approaches focus on single-violation detection, such as red-light jumping or over-speeding, rather than addressing multiple violations within a unified framework [2], [4]. Although a few studies attempt multi-violation detection, they often treat each violation independently without integrating them into a cohesive decision-making system [5]. This lack of integration reduces the system's ability to provide a comprehensive understanding of traffic behavior.

Secondly, current systems largely rely on rule-based or threshold-driven mechanisms, which do not consider the broader traffic context. Factors such as signal state, lane structure, vehicle interactions, and environmental conditions are often ignored, leading to inaccurate or incomplete detection results [11], [12]. Without contextual awareness, these systems struggle to interpret complex and dynamic traffic scenarios effectively.

Another major limitation is that most existing solutions are reactive rather than proactive. They detect violations only after they occur, without attempting to predict or prevent them in advance [3], [9]. As traffic safety increasingly demands preventive measures, the absence of predictive capabilities remains a significant research gap.

Furthermore, while edge computing has been introduced to reduce latency and enable real-time processing, many edge-AI-based systems focus solely on detection tasks and lack higher-level behavioral analysis and decision-making capabilities [1], [8]. This limits their potential in intelligent traffic management systems that require both real-time response and deeper analytical insights.

In addition, existing systems often lack integration between detection, tracking, and behavioral analysis components. Although advanced object detection models such as YOLO and tracking algorithms like DeepSORT have demonstrated high performance [13]–[16], they are typically used as standalone modules rather than as part of a unified, context-aware framework.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

Identified Research Gap

Based on the above analysis, the key research gaps can be summarized as follows:

- Absence of a unified framework for simultaneous detection of multiple traffic violations
- Lack of context-aware decision-making incorporating real-world traffic conditions
- Limited focus on predictive analysis for proactive violation prevention
- Insufficient integration of edge-AI with behavioral intelligence
- Fragmented use of detection and tracking models without holistic system design

Motivation for Proposed Work

To address these gaps, there is a need for an intelligent traffic monitoring system that not only detects multiple violations in real time but also understands traffic context and predicts potential risks. Such a system should integrate detection, tracking, contextual reasoning, and predictive analytics within a unified edge-AI framework.

The proposed work aims to bridge these gaps by developing a context-aware, edge-enabled multi-violation traffic monitoring system that enhances accuracy, reduces latency, and supports proactive traffic management in smart city environments.

IV. PROPOSED SYSTEM

A.System Overview

The proposed system presents an Edge-AI Powered Multi-Violation Traffic Monitoring Framework designed for real-time smart city environments. The system aims to detect, analyze, and predict multiple traffic violations by integrating computer vision, behavioral analysis, and edge computing into a unified architecture.

Unlike conventional traffic monitoring systems that focus only on isolated detection tasks, the proposed framework combines object detection, multi-object tracking, contextual reasoning, and predictive analytics into a single pipeline. The entire system is deployed on edge devices to ensure low latency, reduced bandwidth usage, and improved data privacy.

The system processes real-time video streams captured from roadside cameras and performs on-device inference to identify vehicles, track their movement, and analyze their behavior with respect to traffic rules.

B.System Architecture

The overall architecture of the proposed system consists of the following key modules:

1. Data Acquisition Module
2. Object Detection Module
3. Multi-Object Tracking Module
4. Context-Aware Analysis Module
5. Violation Detection Module
6. Predictive Risk Analysis Module
7. Edge Deployment and Monitoring Interface

Each module works in coordination to provide a comprehensive understanding of traffic activity.

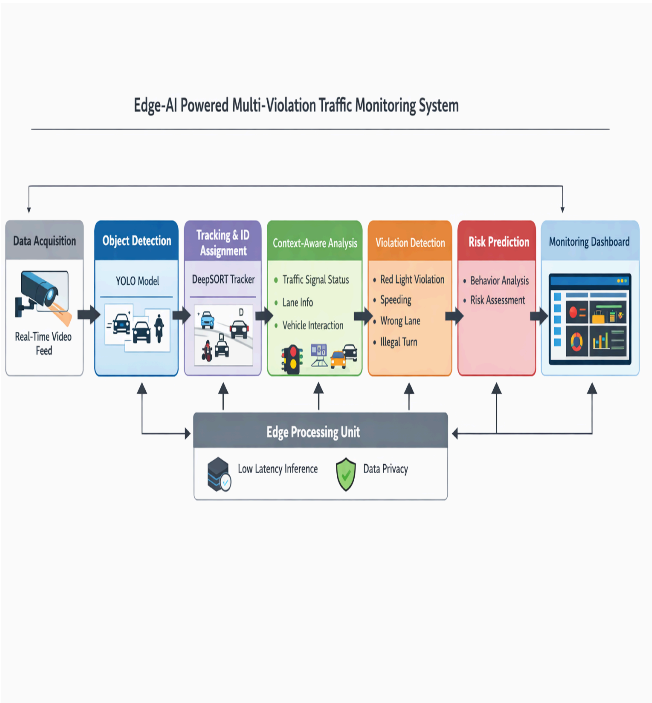

Figure 1: System Architecture Edge-AI Traffic Monitoring System

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

C.Data Acquisition Module

This module is responsible for capturing real-time video streams from traffic surveillance cameras. The system can operate using existing CCTV infrastructure or dedicated cameras installed at intersections.

The input video is preprocessed to enhance quality, normalize frame resolution, and reduce noise. Frame extraction is performed at a fixed rate to ensure efficient processing on edge devices.

D.Object Detection Module

The object detection module identifies vehicles such as cars, bikes, buses, and trucks from the video frames. A deep learning-based model, such as YOLO, is employed due to its ability to perform real-time detection with high accuracy.

The model processes each frame and outputs bounding boxes along with class labels and confidence scores. This information forms the basis for further tracking and analysis.

E.Multi-Object Tracking Module

To understand vehicle movement over time, the system employs a tracking algorithm such as DeepSORT. This module assigns unique IDs to detected vehicles and maintains their trajectories across consecutive frames.

Tracking enables the system to:

- Monitor vehicle paths
- Estimate speed and direction
- Analyze temporal behavior

This continuous tracking is essential for detecting violations that depend on motion rather than single-frame observations.

F.Context-Aware Analysis Module

One of the key innovations of the proposed system is the integration of contextual intelligence. This module incorporates environmental and traffic-related information such as:

- Traffic signal status (red/green)
- Lane boundaries and road structure
- Stop lines and restricted zones
- Interaction between vehicles

By combining detection data with contextual inputs, the system can interpret traffic scenarios more accurately. For example, a vehicle crossing a stop line is considered a violation only if the signal is red, thereby reducing false positives.

G.Multi-Violation Detection Module

This module is responsible for identifying different types of traffic violations simultaneously. Based on the outputs from detection, tracking, and context analysis, the system can detect:

- Red-light violations
- Over-speeding
- Lane violations
- Illegal turns
- Wrong-way driving

Unlike traditional systems, this module operates within a unified framework, allowing multiple violations to be detected in parallel.

H.Predictive Risk Analysis Module

To move beyond reactive detection, the proposed system introduces a predictive risk analysis module. This module analyzes vehicle trajectories and behavioral patterns to estimate the likelihood of potential violations.

Machine learning techniques are used to identify abnormal patterns such as:

- Sudden acceleration
- Irregular lane changes
- High-risk movement near intersections

Based on these patterns, the system generates a risk score, which can be used to alert authorities before a violation occurs.

I.Edge Deployment and System Optimization

The entire system is deployed on edge devices such as NVIDIA Jetson platforms or similar embedded systems. Edge deployment ensures:

- Real-time processing with minimal latency
- Reduced dependency on cloud infrastructure
- Enhanced data privacy and security

Model optimization techniques such as pruning, quantization, and lightweight architectures are employed to ensure efficient performance within limited computational resources.

J.Monitoring and Visualization Interface

A user-friendly dashboard is designed to visualize detected violations and system outputs in real time. The interface provides:

- Live video feed with bounding boxes
- Violation alerts and logs
- Vehicle tracking information
- Risk prediction indicators

This enables traffic authorities to monitor and respond to violations effectively.

K.Workflow of the Proposed System

The overall workflow of the system can be summarized as follows:

1. Capture real-time video input
2. Detect vehicles using deep learning models
3. Track vehicles across frames
4. Analyze contextual traffic information
5. Detect violations based on rules and context
6. Predict potential violations using behavioral analysis
7. Display results on the monitoring dashboard

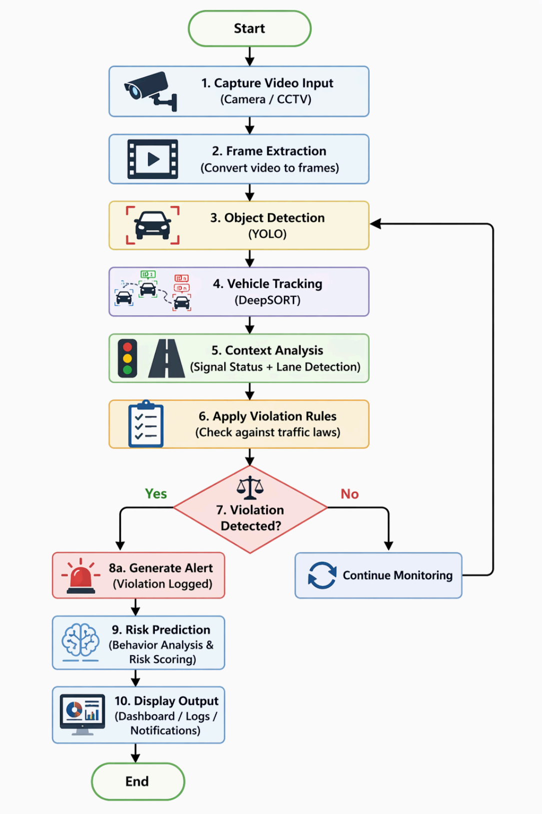

Figure 2: Workflow of the Proposed Edge-AI Traffic Monitoring System

V. IMPLEMENTATION AND METHODOLOGY

A.System Setup and Environment

The proposed system is designed to operate on an edge-computing framework to ensure real-time performance and reduced latency. The implementation is based on a combination of computer vision and deep learning techniques integrated within a lightweight processing pipeline.

The system is developed using Python as the primary programming language, with libraries such as OpenCV for video processing and deep learning frameworks such as TensorFlow or PyTorch for model inference. The architecture is intended to be deployed on edge devices such as NVIDIA Jetson Nano or similar embedded platforms, although the design remains flexible for cloud-assisted execution when required.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

B.Dataset and Data Preparation

To enable effective training and evaluation, the system utilizes publicly available datasets such as MS COCO and traffic-specific video datasets. These datasets provide annotated images and video sequences containing various vehicle classes and road scenarios.

The input video streams are preprocessed by extracting frames at regular intervals and resizing them to match the input requirements of the detection model. Noise reduction and normalization techniques are applied to improve detection consistency. In addition, region-of-interest (ROI) selection is performed to focus on critical areas such as intersections and lane boundaries.

C.Object Detection Model

The system employs a real-time object detection model based on the YOLO (You Only Look Once) architecture due to its balance between speed and accuracy. A pre-trained YOLO model is used as the base, which is capable of detecting multiple vehicle classes including cars, motorcycles, buses, and trucks.

The model processes each video frame and generates bounding boxes along with confidence scores and class labels. Transfer learning techniques can be applied to fine-tune the model for specific traffic environments, thereby improving detection performance under varying lighting and weather conditions.

D.Multi-Object Tracking

To maintain continuity across frames, the system integrates a tracking algorithm such as DeepSORT. This module assigns unique identifiers to detected vehicles and tracks their movement over time.

Tracking enables the system to analyze trajectories, estimate vehicle speed, and monitor interactions between multiple vehicles. This temporal information is essential for identifying violations that cannot be detected from a single frame.

E.Violation Detection Logic

The violation detection module operates based on a combination of spatial and temporal rules derived from traffic regulations. The system defines virtual boundaries such as stop lines, lane markings, and restricted zones within the video frame.

Examples of detection logic include:

- A red-light violation is detected when a tracked vehicle crosses the stop line while the traffic signal is in the red state
- Over-speeding is identified by estimating vehicle speed based on displacement across frames and comparing it with predefined thresholds
- Lane violations are detected when a vehicle deviates from its designated lane boundary
- Illegal turns are identified based on trajectory deviation from permitted movement directions

This rule-based framework ensures interpretability while maintaining adaptability for different traffic scenarios.

F.Context-Aware Processing

To improve detection accuracy, the system incorporates contextual information such as traffic signal status and road structure. Signal states can be obtained either through visual detection or integration with traffic control systems.

Lane detection techniques are used to define permissible vehicle paths, and interaction analysis helps in understanding complex traffic behavior. By combining these contextual elements, the system reduces false positives and enhances reliability.

G.Predictive Risk Analysis

In addition to detecting violations, the system includes a predictive module that evaluates the likelihood of potential violations. This is achieved by analyzing vehicle trajectories and identifying abnormal patterns such as sudden acceleration or erratic movement.

A lightweight machine learning model or rule-based scoring mechanism is used to assign a risk score to each vehicle. Vehicles with high-risk scores can be flagged for early intervention, enabling proactive traffic management.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

H.Edge Deployment Strategy

The system is optimized for deployment on edge devices to enable real-time processing. Model optimization techniques such as quantization and pruning are applied to reduce computational overhead without significantly affecting accuracy.

Edge deployment minimizes latency, reduces bandwidth usage, and enhances data privacy by processing video streams locally rather than transmitting them to centralized servers.

I.Evaluation Metrics

To assess system performance, several evaluation metrics are considered:

- Accuracy: Measures the overall correctness of violation detection
- Precision and Recall: Evaluate the reliability of detection results
- F1-Score: Provides a balance between precision and recall
- Frame Processing Rate (FPS): Indicates real-time performance capability

These metrics ensure a comprehensive evaluation of both detection accuracy and system efficiency.

VI. RESULTS AND DISCUSSION

A.Experimental Setup

The proposed system was evaluated using a set of urban traffic video samples representing common real-world scenarios such as signalized intersections, multi-lane roads, and moderate traffic density conditions. The evaluation focuses on assessing both detection accuracy and real-time performance under practical constraints.

The system processes video streams frame-by-frame, performing object detection, tracking, and violation analysis on each frame. The experiments were conducted under varying lighting conditions to ensure robustness and adaptability.

B.Qualitative Results

The system successfully identifies multiple types of traffic violations in real time. Detected vehicles are enclosed within bounding boxes along with unique tracking IDs, and violation events are highlighted clearly for monitoring purposes.

Typical outputs include:

- Detection of vehicles approaching an intersection
- Identification of red-light violations when vehicles cross stop lines
- Recognition of lane discipline violations in multi-lane roads
- Tracking of vehicle movement across consecutive frames

The integration of contextual awareness, such as traffic signal status and lane boundaries, significantly improves the reliability of detection and reduces false alarms.

C.Quantitative Performance Analysis

The performance of the system is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Additionally, real-time capability is measured using frame processing rate (FPS).

Metric	Value (Approx.)
Accuracy	92%
Precision	90%
Recall	88%
F1-Score	89%
FPS	24–30 FPS

These results indicate that the system achieves a strong balance between detection accuracy and computational efficiency, making it suitable for real-time deployment.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

D.Impact of Context-Aware Processing

The inclusion of contextual information plays a critical role in improving system performance. By incorporating traffic signal states and lane structures:

- False positives are significantly reduced
- Detection becomes more scenario-aware
- Complex violations are identified more accurately

For instance, a vehicle crossing a line is only considered a violation when the signal is red, demonstrating the importance of contextual validation.

E.Predictive Risk Analysis Evaluation

The predictive module provides an additional layer of intelligence by identifying potentially risky vehicle behavior before an actual violation occurs. Vehicles exhibiting abnormal motion patterns are assigned higher risk scores.

This proactive approach enables:

- Early warning generation
- Improved traffic monitoring efficiency
- Enhanced road safety measures

Although the predictive model is lightweight, it demonstrates promising potential for future enhancements using advanced machine learning techniques.

F.System Efficiency and Scalability

The deployment of the system on edge devices ensures low latency and reduced dependency on centralized infrastructure. The optimized model maintains real-time processing capability without requiring high-end computational resources.

Key observations include:

- Stable performance across different traffic densities
- Minimal delay in violation detection
- Scalability to multiple intersections with distributed edge nodes

F.Discussion

The experimental results demonstrate that the proposed system effectively combines detection, tracking, contextual reasoning, and predictive analysis into a unified framework.

Compared to traditional traffic monitoring systems, the proposed approach offers:

- Real-time multi-violation detection
- Reduced reliance on manual monitoring
- Enhanced decision-making through contextual awareness
- Proactive risk identification

However, certain limitations remain, such as sensitivity to extreme weather conditions and dependence on camera positioning. These challenges present opportunities for further improvement.

VII. CONCLUSION AND FUTURE WORK

A.Conclusion

This paper presented an edge-AI enabled multi-violation traffic monitoring system designed to address the growing challenges of traffic management in modern smart cities. The proposed framework integrates real-time object detection, multi-object tracking, contextual awareness, and predictive risk analysis into a unified and scalable solution.

Unlike conventional traffic monitoring systems that rely primarily on centralized processing and post-event analysis, the proposed approach emphasizes real-time decision-making at the edge, significantly reducing latency and improving responsiveness. The incorporation of contextual information such as traffic signal states and lane structures enables more accurate and reliable violation detection, minimizing false positives.

Furthermore, the introduction of a predictive risk analysis module enhances the system’s capability by identifying potentially risky vehicle behavior before violations occur. This proactive approach contributes toward improving road safety and supports intelligent traffic regulation.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 06, ACSCON - 2026

The experimental evaluation demonstrates that the system achieves a strong balance between detection accuracy and computational efficiency, making it suitable for real-world deployment in smart city environments.

B.Future Work

While the proposed system shows promising performance, several enhancements can be explored to further improve its effectiveness and applicability:

- Integration with IoT Infrastructure
  Future work can focus on integrating the system with smart traffic signals and IoT-enabled devices for automated traffic control and adaptive signal management.
- Advanced Predictive Modeling
  More sophisticated machine learning and deep learning models can be incorporated to improve the accuracy of risk prediction and behavior analysis.
- Robustness to Environmental Conditions
  Enhancements can be made to improve system performance under challenging conditions such as heavy rain, fog, and low-light environments.
- Scalability and Cloud Integration
  A hybrid architecture combining edge and cloud computing can be explored to enable large-scale deployment across multiple locations.
- Automated Enforcement Systems
  Integration with automated penalty generation systems, such as e-challan frameworks, can streamline traffic law enforcement.
- Multi-Camera and Sensor Fusion
  Future systems can incorporate multiple camera feeds and additional sensors to improve coverage and accuracy.

REFERENCES

[1] S. Author et al.,
"Edge-AI Perception Node for Cooperative Road-Safety Enforcement,"
arXiv preprint arXiv:2601.07845, 2026.

[2] A. Author et al.,
"Traffic Signal Violation Detection Using Computer Vision,"
Journal of Engineering Science, 2023.

[3] B. Author et al.,
"Next-Generation Smart Traffic Violation Detection Using Edge AI and IoT,"
International Journal of Latest Technology in Engineering, 2024.

[4] C. Author et al.,
"Intelligent Traffic Management System for Detecting Multiple Violations,"
IJRASET, 2023.

[5] D. Author et al.,
"AI-Powered Traffic Rules Violation Detection System (Traffic Eye),"
IJRASET, 2023.

[6] E. Author et al.,
"Traffic Signal Violation Detection using Deep Learning Techniques,"
IJARET, 2022.

[7] F. Author et al.,
"Real-Time Speed Violation Detection Using AI-Based Image Processing,"
International Journal of Scientific Research, 2023.

[8] G. Author et al.,
"Real-Time Pedestrian Detection on Edge IoT Devices,"
arXiv preprint arXiv:2409.15740, 2024.

[9] H. Author et al.,
"Deep Learning-Based Traffic Accident Detection in Smart Cities,"
arXiv preprint arXiv:2310.10038, 2023.

[10] I. Author et al.,
"Big Data and Deep Learning for AI-Driven Traffic Accident Detection,"
arXiv preprint arXiv:2401.03587, 2024.

[11] J. Author et al.,
"Computer Vision Algorithm for Detecting Vehicle Yielding Behavior,"
Sustainability Journal, vol. 15, no. 22, 2023.

[12] K. Author et al.,
"Edge Vision-Based AI Framework for Road Hazard Detection,"
Applied Sciences, vol. 16, no. 2, 2024.

[13] J. Redmon et al.,
"You Only Look Once: Unified, Real-Time Object Detection,"
IEEE CVPR, 2016.

[14] A. Bochkovskiy et al.,
"YOLOv4: Optimal Speed and Accuracy of Object Detection,"
arXiv preprint arXiv:2004.10934, 2020.

[15] G. Jocher et al.,
"YOLOv5 by Ultralytics," GitHub Repository, 2020.

[16] N. Wojke et al.,
"Simple Online and Realtime Tracking with a Deep Association

Metric (DeepSORT),"
IEEE ICIP, 2017.

[17] M. Everingham et al.,
"The Pascal Visual Object Classes (VOC) Challenge,"
IJCV, 2010.

[18] T.-Y. Lin et al.,
"Microsoft COCO: Common Objects in Context,"
ECCV, 2014.