

Smart CCTV-based Bike Monitoring System for College Campuses: Automated Violation Logging and Guardian Notification

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Abstract. Increasing usage of two-wheelers in colleges has brought a lot of safety challenges; non-compliance of wearing helmets, three-wheel riding and unauthorised movement of vehicles, thus the need for intelligent surveillance systems. Traditional surveillance methods are highly dependent on manual monitoring or rule-based vision techniques and thus lack timely response, high manpower consumption and low adaptability to dynamic environmental conditions. To overcome these limitations, a Smart CCTV based Bike Monitoring System (BMS) for detecting and analyzing the violations is proposed and it combines deep learning based detecting the presence of riders, multi-violation analysis, License Plate Recognition (LPR), Real-time Violation Logging and automatic notification of guardians. The proposed system takes live video streams and accurately identifies violations and match to registered vehicles without human intervention. Experimental results show that the detection accuracy achieves 98.9%, the false logging rate is reduced, real-time processing speed is over 40 FPS and notification delay is less than 5 seconds. These results show better reliability, scalability and efficiency towards smart campus traffic safety management.

Keywords: Smart campus traffic surveillance, Two-wheeler violation analytics, Helmet and triple-riding detection, Deep learning-based rider monitoring, CCTV-driven violation logging.

1 Introduction

The growth in consumption of two-wheelers in college campuses has been associated with complex problems on the management of traffic safety. Biking without a helmet, riding two or more persons, over speeding and accessing the campus illegally are some of the common phenomena that pose risks to students, employees and those on the pedestrians. The potential is not being utilized as much as there are high numbers of CCTVs due to man-based surveillance and assessing events that have already happened in the past [1]. The conventional surveillance lacks automation, is sporadic and does not offer real-time response and this translates to enforcement with key lag and little deterrence.

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The latest advances in computer vision and deep learning are also opening new chances to turn passive surveillance into active one and offer the possibility to become the controller of safety and leverage the information as the basis of the decision support [2]. The motivation behind this project is the absence of a solution to the existing campus surveillance systems in the necessity to have a real time, accurate and scalable system of traffic enforcement. Manual observation is tiresome, subjective and tends to cause fatigue, there are high chances of violations being missed and there will be poor generalization [3]. Rule-based vision systems are not reliable in real life situations where the light is dynamic, the vehicles are in motion, and the appearances of vehicles are also changing.

The main aim is to develop an intelligent Bike Monitoring System of CCTV that can automatically identify the violation of the two wheelers regulations within colleges campuses. Some of its features include identification of motorcycles and their riders, helmet and triple riding, identification of license plates and identification with registered vehicle records [4,5]. The proposed system will research the accuracy, the latency and scalability at the limit that the existing CCTV infrastructure will work in varied environmental situations.

The paper facilitates the combined object detection with deep learning and allows detecting various campus-specific violations in the same pipeline. False logging is minimized based on confidence validation and time stability. Automated reporting also ensures accountability is done by ensuring the presence of guardians and authorities who are notified in real time. The rest of the paper is structured as follows: Section 2 will offer related work; Section 3 will give the description of the proposed system; Section 4 will offer results and discussion; and Section 5 will make a closing statement of the paper.

Unlike the existing CCTVs-based Traffic Monitoring Systems in which the focus has been directed towards one of the tasks detections or a deployment to the urban potentials, suggests a combined multi violation detections that is authentic to the campus realms. Likewise, in the same pipeline, it incorporates behavioral analysis of the riders, license plate association and automated guardian notification. Besides, the suggested system accentuates such notions as low-latency processing and privacy-conscious deployment which could be implemented in an institutional setting, which is why they are unique among the common smart city surveillance systems.

2 Related Work

Detection of traffic rule violation using deep learning has been reported to gain traction in isolated settings like the university campus setting. Camera-based systems with CNNs on campus-specific datasets are effective at detecting helmet non-conformance, overloading, and riding in a restricted area, yet most of the solutions are limited to individual types of violations and do not extensively integrate license plate association with automatic response systems.

The methods of detecting helmet violations based on the state-of-the-art object detection framework and data augmentation perform better in the context of generalisation even though occlusions and changing viewpoints are not considered and focuses on the single-violation case, which does not rely on contextual campus regulations or downstream notification processes [6,7]. Smart city infrastructure cloud-based AI real-time CCTV analytics applications meet the needs of urban-scale enforcement cases but cannot be directly applied to campus-focused needs like privacy limits or guard-initiated alarms [8].

Safety monitoring video surveillance with intelligent systems is worth dynamic learning to minimize human errors and response time, and it is hard to transfer such works to dynamic two-wheeler traffic because of motion variability and outdoor lighting variations [9]. Overall reports on helmet detection and license plate recognition plot the way forward

to deep neural networks, but note that motion blur, low-quality plates, and non-standard fonts are still considered barriers to accomplishment [10].

The information systems of student violation tracking focus on discipline logs, administrative reporting in which the data is manually typed, and is not automated with real-time CCTV surveillance of proactive enforcement of traffic safety measures [11,12]. The intelligent surveillance systems that are based on edges demonstrate that it is possible to run deep learning models on low-latency embedded platforms, but the hardware constraint frequently limits the complexity of the model and its accuracy in multi-violation detection environments [13]. Deep learning-based suspicious activity detection systems demand a significant amount of fine-tuning to capture traffic rule semantics in a campus setting [14,15]. The studies have demonstrated successful detection of single violations, like the use of a helmet or the identification of a license plate, most systems are not combined to cover any number of violation categories and are not built in with automated response mechanisms. In addition, the existing approaches are not likely to consider real-time limitations and campus-specific requirements such as privacy and enhanced enforcement. The system proposed counters the limitations discussed above as an end-to-end combined architecture with real time alerting facilities.

3 Proposed System

The proposed structure proposes a smart Bike Monitoring System that relies on CCTV to address the issue of traditional campus traffic surveillance systems, which can be either a manual surveillance system, a rule-based image processing system, or a single violation-detecting pipeline. The systems that are currently used are based on human operators with the traditional machine-vision approaches where manually given features and pre-defined threshold values are used to give a small response rate, many false-positive, thus lower scalability and low robustness under dynamic campus environments.

The proposed solution is a fully automated interface that uses deep learning-based visual processing and real-time surveillance to offer precise, stable and scalable monitoring of a breach of two-wheelers. The system continuously receives live video feeds of the already installed CCTV system and does frame-by-frame processing like resolution normalization, illumination, motion stabilization and correction. A deep convolutional neural network object detection model identifies and classifies motorcycles and motorcycle riders accurately and dataset violation is further sub-divided into helmet non-compliance, triple-riding, and over-speeding and unlawfully entering the premises.

Rather than a single violation type or the necessity of varying pipelines, the multi-class violation detection will be supported by the proposed approach to run with fewer overheads of an inference and reduced latency overheads to conduct in real-time. The inbuilt LPR also processes possible violations and, therefore, recognizes and matches the number plates, retrieves alpha-numeric characters, and compares the findings with the central vehicle database. False recordings are reduced to minimum using validation with confidence and temporal consistency checking.

Upon identification of proven violation, the system records the incident as a visual recording that is both time stamped and that the record has an alert system which triggers an alert in school authorities/guardians via SMS/email without the activation of the notification mechanism controlled by the system. An administrative dashboard offers the possibilities to track in real-time, the past analysis of violations, and create reports. The general system provides coherent implementation, positive reinforcement of the safe riding habits and can be extended to the campus facilities utilizing the existing CCTV systems.

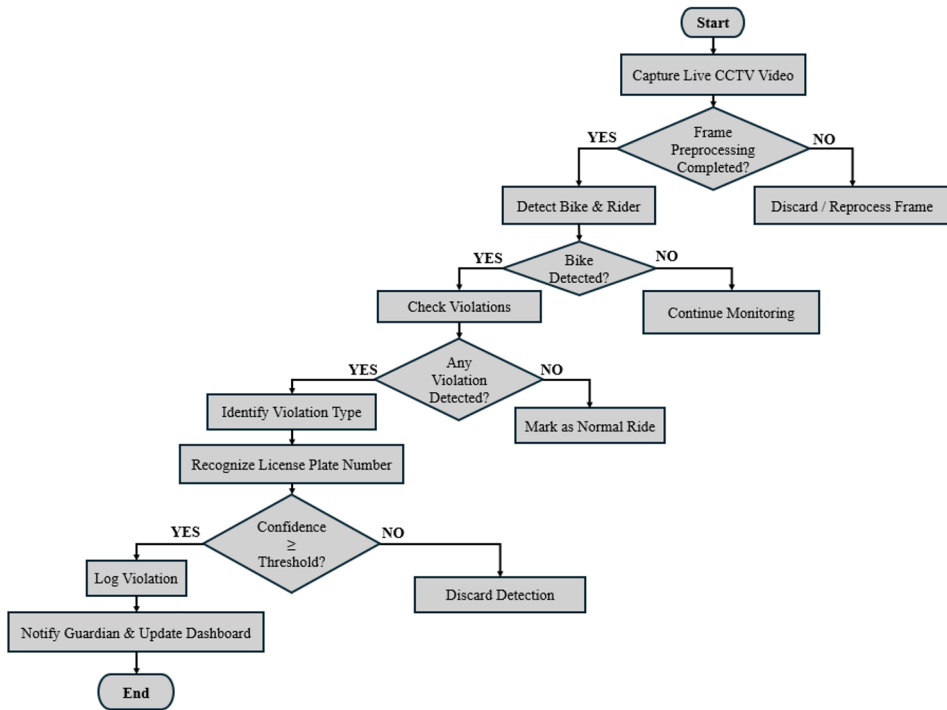


Fig. 1. Decision flow for smart CCTV-based bike monitoring system.

The entire process begins with the video capture of the CCTVs and followed by the preprocessing to enhance the picture frame quality of the video. The resulting processed frames are then fed through a YOLO based detection model to identify motorcycles and riders. Violations like lack of a helmet and triple riding are investigated on detected objects. The license plate recognition module reads vehicle numbers on the vehicle and compares the numbers to a centralized data bank. Lastly, when there is valid violation, these are logged down and real-time notifications are sent to the guardians and authorities. For this study, dataset used in training the CNN model was obtained from Kaggle Dataset.

3.1 CCTV Video Acquisition and Frame Extraction

The proposed system will begin by receiving live video feeds of the fixed CCTVs at the various points within the campuses such as the gates, the roads within the campuses, the parking lots. Video streams are decoded into sequences of fixed-rate frame sequences, which are received and processed following the Real-Time Streaming Protocol, and decoded in accordance with the trade of the time resolution and computing labor. Frame sampling method keeps the continuity and at the same time eliminates redundant frames. The frames extracted are all unanimously up sampled to a fixed input resolution as required by the deep learning models, thus making the data uniform in case of multiple camera inputs. The cameras are time synchronized in such a way that they capture the violations and to synchronize the time of cameras. The sample of data will be the CCTV images of different locations within the campuses including gates, car parks and inner roads. It has pictures of motorcycles and riders with remarks, and they are in various weather and light conditions along with the helmet and license plates. The data will be divided to form training (70 percent), validation (15 percent) and testing (15 percent) in order to realize a high model testing.

3.2 Image Preprocessing and Quality Enhancement

Preprocessing is used as a technique of acquiring improved visual quality and environment variance resistance. The adaptive histogram equalization is used to bring the lighting to a normal level and brings contrast to dark or darkened areas. To reduce noise in the sensor, a Gaussian filter is applied still preserving edge data which is used to outline objects. The motion blur is repaired with a frame-differencing and sharpening filters to give clarity on the situation when automobiles are in motion. Color normalization eliminates the variations in the cameras with various characteristics of calibration. Background suppression techniques reduce the undesired information in a picture besides enhancing sensitivity of the objects in the foreground. The combination of these preprocessing steps enhances the discrimination and elimination of false detection and stability of model inference under a wide range of conditions on campus such as rain, glare, partial occlusion and night surveillance.

3.3 Two-Wheeler and Rider Detection Using YOLO

The object detection model is a YOLO (You Only Look Once) object detector which will be utilized in the detection of motorcycles and riders in real-time in a video of a campus surveillance. YOLOv8 was also modified in this work because this is more accurate, faster to perform inference and features are better represented than older ones. YOLOv8 is also a single-stage-detector, therefore, it can localize and classify objects in a single forward pass, hence, it is suitable to apply to the real-time scenario. The system comprises of convolutional backbone in the feature extraction, multi-scale feature aggregation neck and bounding box prediction and classification detection heads. This design allows appropriate identification of various objects at diverse situations at the campus such as obstruction, light change, and traffic congestion. Training of the model is then performed using transfer learning and the initial pre-trained weights and then fined on a custom dataset of annotated campus images. The data set includes diversity of situations, i.e. different perspectives, lighting, and riders' arrangement. The training is carried out with a batch of 16, learning rate of 0.001 and 100 epochs. In order to improve generalization, data augmentation algorithms, including rotation, scaling and flipping, are employed. The trained model will be able to achieve the recognition of multiple riders on the same vehicle such that the violation analysis, such as the triple riding and the helmet detection are able to be applied in reality.

3.4 Helmet and Triple-Riding Violation Detection

Helmet and triple-riding violations are detected through spatial and contextual analysis of detected riders. Helmet detection uses a CNN-based binary classification model trained on cropped head-region images obtained from rider bounding boxes. The model trains discriminative feature representations using the shape, texture, and color pattern of the helmets thus resilient with respect to the feature classification in the instance of partial obscuration. Triple-riding verification is done to perform an enumeration and to count the number of triples of a rider which are contained by a bounding box of a motorcycle in accordance with the intersection-over-union association rule. Ensure Temporal consistency Checking Temporal consistency ensures that neighbouring frames include the same packet, without considering transient miscounts that happen as a result of misocclusions or flicker during detection. These algorithms collaborate to detect multiple violations across different safety constraints in a single inference cycle, enabling high efficiency in identifying compound violations common in campus traffic. The formulation of helmet detection is

based on binary classification problem, in which the input data is a cropped head on a detected rider bounding box. Let I is the input image region and the classifier is the predictor of label. $y \in \{0, 1\}$ $y=0$ or 1 , 0 = no helmet and 1 = helmet. Triple riding detection is done by the number of rider bounding boxes on a single motorcycle matched by Intersection-over-Union (IoU). When the number goes above two, it is considered a violation.

3.5 License Plate Detection and Recognition

License Plate Recognition (LPR) is carried out using a two-stage system including detection and Optical Character Recognition (OCR). Plate detection is performed by a deep learning-based object detector trained specifically for Indian license plate formats covering various fonts, sizes, and mounting positions. Detected plate regions are geometrically corrected using perspective transformation before character recognition. Character recognition employs a deep sequence recognition model consisting of convolutional layers with a Recurrent Neural Network and Connectionist Temporal Classification loss. Training data is synthesized by augmenting plate images to generate noisy, blurry, and low-resolution inputs. Confidence scoring and checksum verification mitigate recognition errors. Verified plate numbers are checked against a centralized vehicle database to link violations with related student information. The version of CRNN (Convolutional Recurrent Neural Network) architecture and CTC loss sequence prediction is used to implement Optical Character Recognition (OCR). To make the model more noise and blur resistant, the model is trained on both synthetic and real license plate data.

3.6 Violation Logging and Guardian Notification

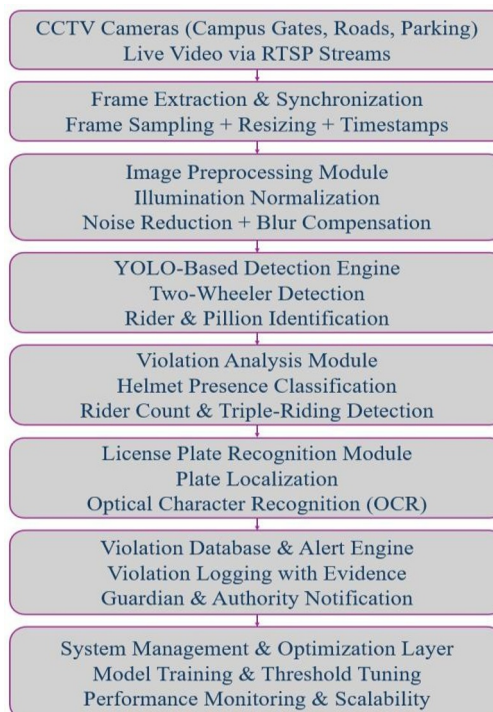


Fig. 2. Smart CCTV-based two-wheeler violation detection architecture.

The violations detected are automatically inserted into an automated central database containing metadata of the type of violation, date and time of violation, position of the camera, car number and annotated picture of the violator. False alarms are kept at minimal levels and only high-confidence detections are carried on ruling based validation layer. In the event of established logging, an automated notification of violation using SMS and email disseminates the information regarding violations and sends a picture of violations to register parents and college officials. The rate limiting policy and rate escalation policy prevent alert storms and offer. The data concerning the previous violations will be in quick retrieval format that will facilitate the trends analysis. The use of automated logging and notification to eliminate the human input allows real-time application and data-driven management of college safety.

3.7 System Integration, Training, and Performance Optimization

The whole system is modularly architecture based to execute video streams simultaneously. Transfer learning is used to train models faster and ensure higher performance on small datasets specific to the campuses, in model training. Hyperparameter optimization trades accuracy and speed when detecting threshold, learning rates and batch sizes. The model compression techniques can be used to perform inference in real-time on edge or mid-range GPUs. Accuracy, precision, recall, frame processing rate, and notification latency measures are used in the evaluation of performance continuously. The integrated system ensures that it is scalable to multiple cameras and areas of the campus with uniform high performance over a long duration of smart campus implementation.



Fig. 3. Real-time traffic violation detection with license plate extraction.

In conclusion, the monitoring system using the Smart CCTV has already been the effective and scalable approach to the improved safety of the college campuses. It also enforces easily and in consistency with automatic violation detection, workable license

plate recognition, and real-time guardian alert. The experimental results confirm the opinion that the method helps to save the significant part of the manual control, and it can be applied to the scenario of intelligent campus traffic management.

4 Results and Discussion

The efficiency of the proposed system in surveillance of bike violations is supported by the comparison of the suggested approach to two state-of-the-art deep learning-based campus traffic surveillance systems. The evaluation of performance is done with such criteria as detection accuracy, precision, recall, processing time and alert delay, which depend on the strength, real-time performance and scalability to large academic campuses.

System	Overall Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
P. Chaturvedi et al. [6]	96.8	95.9	94.6	95.2
M. Shoman et al. [7]	97.4	96.8	95.9	96.3
Proposed System	98.9	98.2	97.6	97.9

Table 1 compares the efficacy of violation detection utilizing classical measures of classification. Existing System [6] is also effective in identifying the violation of the rule at the campus level, but it is less recollective when there is occlusion and heavy traffic. Existing System [7] would increase uniformity in the identification, where the system comprises the learning where the helmet is oriented, however, is constrained to the specific sort of violations. By learning patterns of multiple violations, the proposed model can be more accurate and achieve a higher balance between precision and recall of different violations, including helmet non-compliance, triple riding, and unauthorized entry. The F1-score is higher, which means that it is detected consistently across various campus configurations.

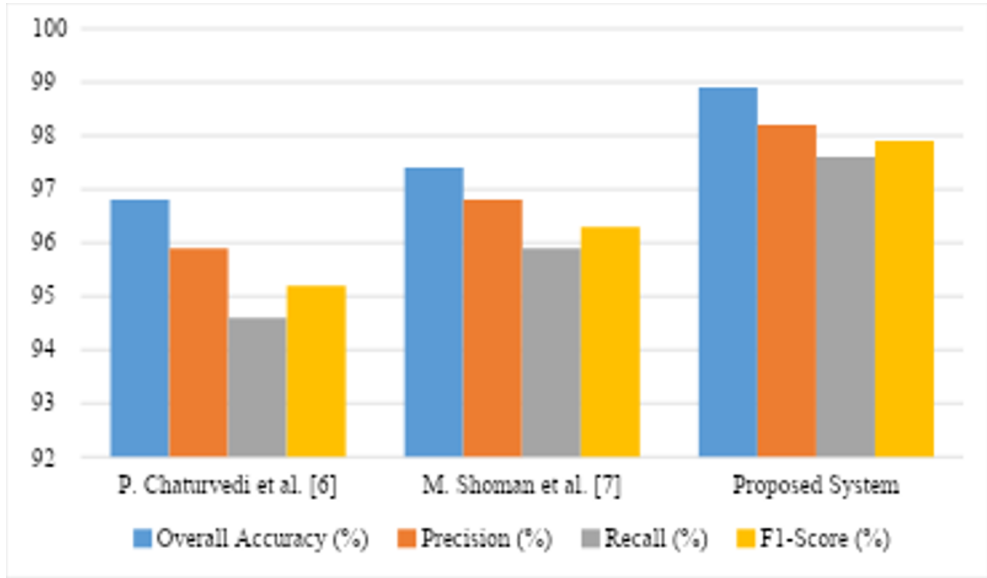


Fig. 4. Visual plotted view for violation detection performance comparison.

The Table 2 compares the accuracy of LPR and logging efficiency of violation. The existing systems use the traditional OCR pipelines which are not efficient in low illuminations and motion blur, and this increases false logging rates. Existing System [6] is middle rate with apparent mis-association at peak times whereas existing system [7] gradually enhances the detection stages with increased computational cost. The offered system significantly enhances the quality of recognition and minimizes false logs via the adaptive preprocessing and confidence-based validation. The lowered time taken to process a frame indicates a higher level of real-time performance, which allows the continuous monitoring of the campus.

Table 2. License plate recognition and logging efficiency.

System	LPR Accuracy (%)	False Logging Rate (%)	Avg. Processing Time (ms/frame)
P. Chaturvedi et al. [6]	94.1	6.3	38
M. Shoman et al. [7]	95.6	5.1	35
Proposed System	97.8	2.4	29

The Table 3 shows the real-time responsiveness and administrative load. The previous methods offer nearly real time processing but have a long manifestation period on sequence validation and review procedures. System [6] only shows average performance in the supervision burden, but system [7] yields better results in responses but does not include automated notification integration. With the exploitation of a fully automated end-to-end pipeline, consisting of detection up to guardian alerts, the suggested system will have a higher frame processing rate and will decrease the notification delay many folds. The reduction of the manual overhead is significant to the extent that it enables scale effect, and transparent and timely implementation of the campus traffic control.

Table 3. System Responsiveness and Operational Impact.

System	FPS (Real-Time)	Notification Latency (s)	Manual Intervention Reduction (%)
P. Chaturvedi et al. [6]	32	12.5	55
M. Shoman et al. [7]	36	9.8	63
Proposed System	44	4.2	78

These experimental results confirm the fact that vision-based intelligent inspection system could be employed in the reliable separation of the types of violations provided the conditions of the surface and environmental factors varied which proves its high grade of generalization. The quality of the inspection is stable and predictable because the features that are extracted are dissimilar between genuine violations and ordinary traffic variations with the assistance of the deep learning-founded features extraction. The system may be employed in the campuses traffic environment where real-time monitoring of the traffic is constant and the data utilized in the inspection can also be archived to streamline the procedure, to make a trend and predict the safety management in alignment with the smart campus goals.

The system will make sure that the surveillance data are utilized with utmost safety enforcement in the campus premises. Any information obtained is kept under lock and key and access to this information is only allowed to authorized personnel. Personal data is processed according to the policies of data protection, and the notification systems are fashioned in a way that will preserve the transparency without infringing on the personal privacy.

5 Conclusion

In conclusion, the proposed Bike Monitoring System, which is based on Smart CCTV is a decent and scalable tool to enhance the degree of traffic safety in the college campuses. The system can monitor and enforce two-wheeler regulations in real-time and combines deep learning object detection, multi-violation analysis, license plate recognition, and automated notification systems. You are sure that motorcyclists and riders will be identified in the specified conditions irrespective of the environment as the YOLOv8 is used, and the processing latency is reduced to the minimum since only one pipeline is used, no human supervision is needed. The results of the experiment indicate that the detection would be high, the false logging would be less, and the system would be able to produce alerts quickly, which indicates that the system is trustworthy and could be used in the dynamic campus environment. Despite these advantages, there are other disadvantages. Quality annotated data is a key determinant to the performance of the system but its acquisition and maintenance may be costly. Additionally, extreme lighting, motion blur or occlusions can all operate on the detectability. Deployment on low-resource hardware may also be considered as addition of computational constraints. The future research must be aimed at enhancing the model with the help of semi-supervised learning methods to minimize the use of annotated data. Moreover, it should be aimed to improve performance in adverse environmental conditions and to streamline models to be deployed on the edges. In the real life, one can make the system more flexible and expand it to multi-modal and continuous learning to increase the long-term adaptation and performance.

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