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AI-Driven Surveillance for Helmet Detection and Number Plate Recognition

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***Abstract*— As the cases of two-wheelers on roads brought with it surge in helmet violations, which makes monitoring systems important that are automated. This study deals with automatic detection system for helmet violation detection with Automated Number Plate Recognition. A YOLOv11m object detection model act as backbone, dividing motorcycle riders as helmeted or non-helmeted then locating number plates within live CCTV footage.**
To reduce computational overhead, selective ANPR mechanism is mentioned, where Optical Character Recognition (OCR) is executed when rider without helmet is trapped. This mechanism minimizes unnecessary computation and enhances overall system efficiency. The model is trained on custom dataset of 8,460 labelled traffic images captured under different illumination, different camera angles, occlusions, and different traffic densities.
Experimental results show a mean Average Precision (mAP@0.5) of 95.3%, helmet detection precision of 92.9%, and number plate detection precision of 95.5%, with real-time processing speed of 56 FPS. Comparative evaluation against YOLOv5 and YOLOv8 demonstrates the superior performance of YOLOv11m in crowded urban traffic scenarios. The proposed system can be deployed in smart city surveillance, e-challan generation, and automated law enforcement systems.

***Index Terms*—AI-driven automated surveillance, Automatic Number Plate Recognition, CCTV, DNN, e-challans, Helmet Detection, Optical Character Recognition, YOLOv11.**

I. INTRODUCTION

Road safety has been a significant challenge for the global community, especially for any country where there is a high concentration of two-wheelers. The scooters and motorcyclists are considered to be the most vulnerable users of the roads since they have little physical protection and the fact that they are not wearing protective helmets would make them very vulnerable to fatal head injuries. Although there are stringent traffic rules that require the use of helmets, this has not been met with compliance particularly in the high populated urban regions. Traditional enforcement systems are based on manual inspections at the roadside or human observation over surveillance video which are time consuming, subject to error and ineffective on scale [1].
Smart cities have opened opportunities in automated monitoring of traffic as a result of the rapid establishment of Closed-Circuit Television (CCTV) infrastructure. Nevertheless, it is very difficult to draw actionable intelligence out of the continuous video stream on real time [2][3].

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Manual surveillance is inefficient when dealing with a lot of video data and the traditional image-processing based methods are not robust when dealing with real-world scenarios such as large amounts of illumination, occlusions, motion blur and complex background. These restrictions show that there should be smart, automated solutions that can effectively identify traffic violations with minimal human effort.The recent development of deep learning and computer vision has allowed the detection of objects in real time to make important progress. The balance of accuracy and speed has made Convolutional Neural Networks and one-level object detectors like YOLO series has proved very useful in resolving this issue in traffic management applications[4]. However, most automated helmet detection agencies work to ensure proper use but lack a reliable correlation between infractions and car identification. In addition, some ANPR systems are used in module, with less design for integrating automated enforcement procedures [5].
Therefore, to demonstrate these challenges, this study proposes an integrated multi-purpose AI surveillance scheme which is capable of detection of helmet violations and detecting number plates in single system. As such, the proposed system will employ a customized YOLOv11m algorithm for detecting riders, detecting the presence of helmets, and detecting vehicle plates in CCTV frames. Unlike existing mechanisms that constantly monitor all traffic by using ANPR, the proposed system will employ a violation-based mechanism in which detection of the number plate is only conducted when there is a helmet violation. This chosen activation is both efficient in computation and real-time[6][7].

II. MAJOR CONTRIBUTION

The main observations of this study are as follows:

- AI-Driven Traffic Surveillance framework: This study suggests a completely automated, real time monitoring single system of the integration of helmet violation and Automated Number Plate Recognition to enforce intelligent traffic. In contrast with independent methods of monitoring rider safety, the system provides a direct connection between compliance and vehicle identification, which makes it possible to generate evidence about a violation[8][9].
- Fine-Tuned YOLOv8 in Helmet and License Plate Detection: To perfectly identify a helmet and number plate, cases of non-helmet, and vehicle license plates in complicated urban settings, a YOLOv8 object detection the neural network is trained using a traffic tracking dataset. Optimization of the model is gained in identifying tiny objects in complex situations including occlusion, motion blur, and changing illumination[10].
- Violation Triggered ANPR Pipeline: In order to improve computational and real-time performance, this studyproposes a violation-triggered ANPR that implements license plate recognition and OCR when a helmet violation detected. Such chose processing reduces irrelevant inference and enhances scalability of system.
- Indian Traffic Scenario Annotated Dataset: A dataset containing 8,460 annotated images is curated and labeled for helmet, no-helmet, bike, and number plate classes, framing real world Indian traffic situations. The data can be used to conduct a strong training and testing phase and counteract the deficiency in datasets that would facilitate two-wheeler safety tracking in specific area.

III. RELATED WORK

A. Helmet Detection using Deep Learning

Existing helmet detection mechanisms depends on image processing technologies such as color segmentation, edge detection,and handcrafted features. These processes were unreliable in real scenarios. Deep learning models such as CNN,SSD, Faster R-CNN, and YOLO constantly enhanced detection accuracy. YOLO-based methods are suitable for real-time traffic surveillance due to single-level detection and rapid inference.Object detection systems have been developed as a result of the introduction of deep learning. SSD and YOLO are quicker than Faster R-CNN, and have a higher detection output.

B. Automatic Number Plate Recognition

ANPR is also an important element of intelligent transportation systems and has been widely researched in vehicle identification and vehicle tracking. The traditional ANPR systems typically involve localization of license plates, Characters segmentation and Optical Character Recognition (OCR). OCR models are more suitable although the detection model based on Deep learning technology improves accuracy in localization of license plates, OCR models still affected by the font type, the lighting, the motion blurs, and the camera angles.

C. Integrated Traffic Violation Detection Systems

A number of recent papers have tried to integrate helmet detection with number plate recognition in aiding automated traffic law enforcement. Those systems show that it is possible to connect the safety breaches with the vehicle identity through OCR and deep learning-based object detection methods. However, available solutions typically run ANPR processing on all identified vehicles continuously, which raises the computation costs and reduces scalability in real-time.

IV. METHODOLOGY

This section outlines the suggested AI-based framework to be created to detect helmet violation in real-time and the automatic recognition of vehicle number plates based on traffic surveillance videos. The system is modeled as a pipeline where the non-compliance of the helmets is detected, the vehicle number plate related to the non-compliance is extracted and organized records of the violations are formed which would be utilized in the enforcement of traffic.

A. Data Acquisition and Annotation

The dataset was comprised of around 17,000 images, which were obtained from Roboflow. The dataset contained varied environmental settings, including daylight, night, low-light, and shadowed environments. The images were taken from various angles of the camera to make the model more robust. The dataset was also checked for any inconsistencies in the annotations to make sure that the bounding box annotations in the YOLO format were accurate. In order to train the proposed system and evaluate it, a dedicated dataset was built based on publicly available data of traffic surveillance and the randomly selected video frames. The data comprises of 8,466 annotated images of varied real-world traffic situations, the changes in lighting, camera positions, occlusions, and rider positions. The images were manually annotated with the Roboflow annotation tool in each of the four classes, namely, helmet, no-helmet, bike, and number plate.

B. Helmet Detection Using YOLOv11m

A finely-tuned YOLOv11m object detection model is used to implement the helmet detection module. YOLOv11m is the best method due to its optimized single-stage detection architecture that incorporates effective feature extractions together with attention-based mechanisms that allow the precise localization of small objects like helmets in the busy traffic conditions. YOLOv11m was chosen because it has a better trade-off between detection precision and efficiency than its predecessors, YOLOv5 and YOLOv8. YOLOv11 also features anchor-free prediction strategies, which enhance localization precision and efficiency compared to the predecessors, which used anchor-based prediction strategies. The medium(m) model was chosen because it has higher precision than the nano and small models but still supports real-time processing. Input frames are resized to 640 x 640 pixels and processed in a single forward pass Predicts bounding boxes and class probabilities simultaneously. The "Fig 1. Architecture of Helmet Detection" uses a single-stage detection mechanism.

C. Violation-Triggered Number Plate Detection and Recognition

To make it more computationally efficient, number plate recognition is enabled in case there is a no-helmet violation. After the detection of a violation, the vehicle region is localized, and the license plate area is extracted also with the same YOLOv11m detector.

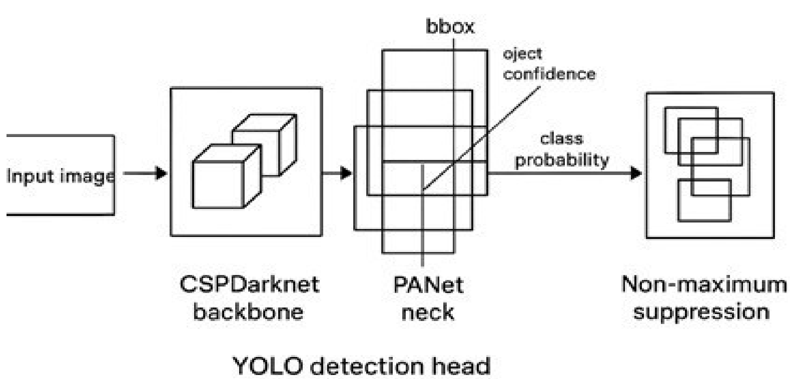

Figure 1. Architecture of Helmet Detection YOLOv11m Model

The cropped license plate Convert the image to a grayscale image and resize and noise-reduced in preprocessing operations, which aim at making the characters more prominent. An OCR is then used to read the vehicle registration number in alpha numeric. This violation-determined approach minimizes the unwarranted OCR processing and allows real-time deployment, which can be expanded.

D. Training and Evaluation

The YOLOv11m was trained on the Google Colab (GPU enabled environment) for 50 epochs, with a batch size of 16, and an initial learning rate of 0.001. SGD was chosen as the optimizer during training, and the cosine learning rate schedule was utilized to ensure stability of convergence. Object detection metrics such as precision, recall, and mean Average Precision(mAP@0.5) were used to evaluate performance. The speed of inference was reported using the unit of measure frame per second (FPS) to determine the viability of real time inference.

E. System Architecture and Workflow

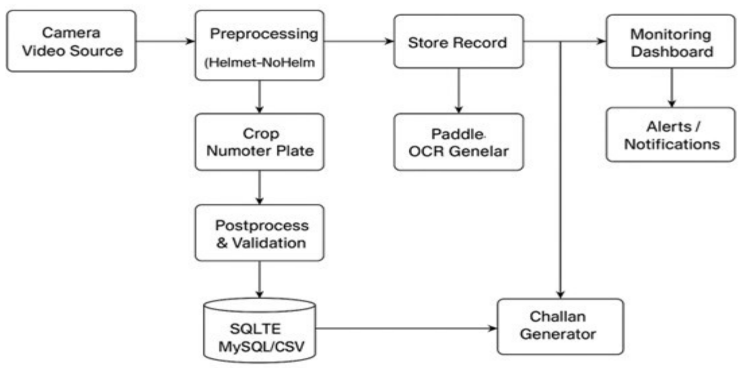

Figure 2. Workflow of Model

The "Fig 1. Model Architecture" proposed AI-Driven Surveillance for Helmet Detection and ANPR is supposed to detect helmet violations and automatic vehicle recognition in a sequential and modular process. The system workflow is presented in "Fig. 2 Workflow of Model" and is explained as follows.

- Image/Video Frame Acquisition: Live video footage of the CCTV cameras or an already recorded footage of traffic is sampled on a frame-by-frame basis. The individual frame is sent to the detection module of further processing which allows it to monitor continuously in real time.
- Helmet Detection and Violation Identification: The fine-tuned YOLOv11m model processes every input frame and identifies riders and determines the use of helmets. Riders who are spotted without helmet are registered as violation cases and this initiates further processing.
- Number Plate Detection and Extraction: In the case of violations of helmet, the area of the vehicle is scanned on which the license plate is localized. The plate region detected is clipped out of the original frame to obtain a focused input to the recognition.
- Optical Character Recognition (OCR): License plates have been previously numbered to improve the clarity of characters and forwarded to the OCR module where the alphanumeric registration number is extracted. This process is used to translate the visual evidence into machine readable.
- Violation Logging and Evidence Generation: Every confirmed violation is documented with the corresponding metadata that contains the time of it, vehicle number that was identified, and the image evidence. The organized records enable automated reporting and additional interface with the traffic enforcement systems.

F. Integration and Deployment

All the experiments had been performed on system with Intel i7 processor, 16GB RAM and NVIDIA RTX 3060 GPU. The average speed of the model on input images with the resolution of 640×640 was 22 FPS. The trained detection and Face recognition models were integrated in a Flask-based app. It takes only video feed as an input and draws bounding boxes around the objects which it has detected as violations and confidence scores. All violations detected will automatically be recorded tagged with time stamp, registration numbers and photos of the violations.

V. RESULTS AND DISCUSSION

In this section, we analyze the results of the project thoroughly the suggested AI-powered helmet detector and number plate recognition system. The fine-tuned YOLOv11m model and the combined OCR-based ANPR pipeline are evaluated using accuracy of the detection and their robustness and feasibility in a real-time scenario.

A. Helmet and Number Plate Detection Performance

The detection performance of the YOLOv11m model was evaluated separately for each object class, including helmet, no-helmet, bike, and Precision, Recall and mAP@0.5 were utilized as metrics of performance. A detailed per-class performance analysis is shown in "Table I. Per-Class Detection Results". Each class's individual metrics (Precision, Recall, and mAP@0.5) are computed separately to evaluate category-wise consistency of the model.

TABLE I: PER-CLASS DETECTION RESULTS OF YOLOV11M MODEL

Class	Precision	Recall	mAP@0.5
Bike 0.897	0.904	0.962	
Helmet	0.929	0.892	0.942
No Helmet	0.922	0.870	0.922
Number Plate	0.955	0.950	0.978

The fact that the number plate detection accuracy is high also reiterates the appropriateness of the model in downstream processing of OCR. The OCR module was tested for accuracy based on both character-level and full-plate recognition. The character-level accuracy was measured by Confusion matrices were analyzed based on the ratio between correctly recognized characters and the total number of characters, which resulted in an accuracy of 97.2%.

C. Mean Average Precision (mAP) and Training Behavior

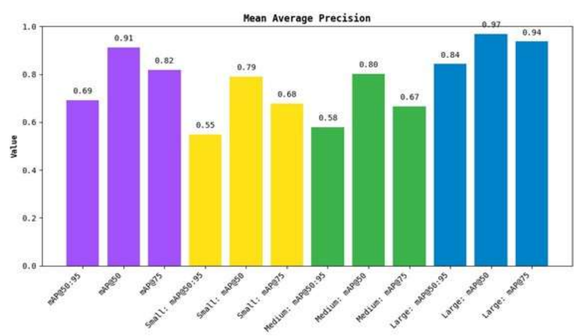

Figure 3. Mean Average Precision

The model achieved an overall mAP@0.5 of 95.3%, indicating reliable object localization and classification. From the above "fig 3. Mean Average Precision" it can be seen that the model converges into no diverge, thus confirming the proper generalization ability of the model on unseen datasets.

A. Precision-Recall and Confidence Analysis

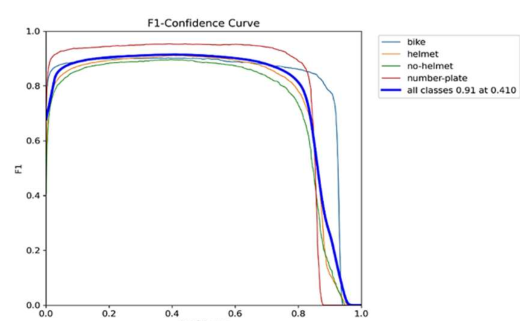

Figure 4. F1-score variation with confidence threshold for all detected classes.

To validate the detection ability of the proposed algorithm, precision-recall and confidence-based performance curves were examined across all classes of objects. The “fig 4. F1-confidence curve”, also identified the best confidence level at which to deploy. As indicated in the curve, the highest F1-score of about 0.91 is obtained at a confidence level of about 0.41 which reflects a moderate trade-off between precision and recall. This value guarantees good sensitivity to the violations as well as the minimal false positives which is vital in real-time traffic monitor systems.

B. Real-Time Performance Evaluation

Inference rate is one of the most important aspects that should be considered for practical use. For the proposed framework, an average inference rate of 56 FPS was achieved on hardware with connected GPUs, which is adequate to run in real time operational requirements of live CCTV feeds. The ANPR strategy based on violation further minimized the computing cost by restricting OCR to the relevant frames, improving scalability when deployed on large scale.

C. Comparative Evaluation with YOLO Variants

In order to prove the efficiency of YOLOv11m, it was compared with the models of YOLOv5 and YOLOv8 with the same dataset and the evaluation protocol.

TABLE II. COMPARISON OF YOLO ARCHITECTURES

Model	mAP@0.5 (%)	Precision (%)	FPS
YOLOv5	89.4	88.6	42
YOLOv8	92.1	91.7	49
YOLOv11	95.3	94.8	56

The above “Table II. Comparison of YOLO Architectures” indicate that YOLOv11m outperformed others when it comes to accuracy of detection and speed. This can be explained by the fact that the improved feature extraction and attention mechanisms in YOLOv11m help to enhance. The system can effectively detect small object such as license plates and helmets in crowded places.

D. OCR Accuracy and Violation Identification

The OCR-based ANPR module successfully extracted vehicle registration numbers from detected license plate regions with high accuracy under favorable lighting conditions. Occasional recognition errors were observed in cases involving blurred plates, extreme angles, or low-resolution frames. However, integrating preprocessing techniques consistently enhanced character detection reliability, making the system suitable for automatic helmet rule violation logging.

E. System Integration and Real-Time Evaluation

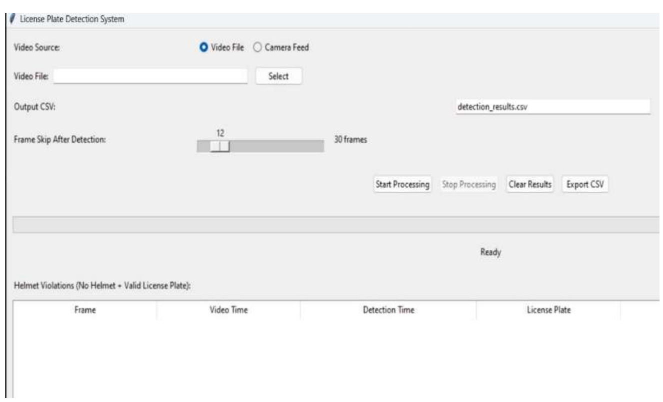

Figure 5. System Integration and GUI

The above “Fig 5. System Integration and GUI” offers a convenient method for seeing live helmet detection and number plate recognition. A real-time surveillance application was created with trained YOLOv11m detection model and OCR-based ANPR module to assess the performance of the end-to-end system. It takes live or recorded video streams of traffic and superimposes the results of the detection, such as helmet status and localization of the license plate, on each frame.

F. Detection and Recognition

To prove the effectiveness of the integrated detection and recognition pipeline, it was tested on actual video sequences of traffic. The violations with helmet were properly detected and drawn attention, and the number plates were also localized and identified using the OCR module. The detection was found to be successful at different traffic densities and lighting conditions. Certain cases of recognition errors were observed in the cases of severe motion blur or partial occlusion, but the system was able to find violations in all the cases, which guarantees the reliability in generating evidence.

G. Qualitative Analysis and Error Discussion

The qualitative analysis of actual video traffic flows in reality shows that the system effectively identifies helmet offences and identifies them with the car number plates properly. Occurrences of failure are mostly seen in the difficult case of severe occlusion, poor night illumination, or the case of helmets which match background colors. These issues can be improved further by means of supplementary training information and greater preprocessing techniques.

Figure 6. Detection of Rider Without Helmet and Number Plate Recognition

The "Fig. 6 Detection of Rider Without Helmet and Number Plate Recognition" shows that the developed system detected a traffic violation correctly, utilizing the YOLOv11m model for detection. The bounding box shown in red labelled 'no helmet' encloses the head of the rider, confirming that the rider was not wearing a helmet. Also, as seen in the diagram, the vehicle's number plate has been detected and shown with a bounding box in blue color, thereby confirming the effective localization of the object by the model.

H. Discussion

The outcomes of the experiment show that the suggested system is effective to address the gap between helmet detection and vehicle identification within a single system. The violation-triggered ANPR strategy is more effective than the current methods, as it is more efficient and yet the accuracy is high. The real-time performance of the systems, along with the evidence generation based on them, makes it an interesting method to use in practice in the sphere of smart city surveillance and intelligent traffic enforcement.

VI. Conclusion and Future Work

This paper presents an artificial intelligence-based surveillance system aimed at the automatic detection of helmet violation and plate number and an ANPR OCR pipeline. Practical observations denotes that it has high detection, strong real-time performance, and can be easily integrated to make an effective traffic-monitoring software. Beside a better performance qualities, there were some cons to be found in abnormal situations like poor illumination, strong motion blur, and half covering. Future work will focus on enhancing the performance of night-time motion detection using the infrared-based imaging and the sophisticated image improvement methods. The model generalization can be further improved by enhancing the range of the training data with various weather conditions and camera positions. Besides, incorporating a time tracking and multi-camera integration can lead to the enhancement of consistency of violation and fake detection. Automatic e-challan creation and real-time connection with traffic management systems can also be extended to the system.

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