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A Deep Learning-Based Framework for Automatic Helmet Violation Detection and Number Plate Recognition Using YOLOv8 and OCR

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Abstract — Violations of traffic laws, specifically the non-use of helmets by persons on two-wheelers, still form the major cause of deaths in India. Manual surveillance by traffic law enforcement agencies is inefficient, time-consuming, and error-prone. In this paper, we propose an automated NAS-BACKBONE, YOLOv8, and Full Frame OCR approach to identify helmet violations and vehicle number plate images from video footage. YOLOv8 is used to classify helmets, and Full Frame OCR is used to recognize the number plates containing text. The database is an in-house-developed RTO format CSV database to authenticate vehicle ownership. Streamlit is used to provide the graphical interface to classify and record the helmets and vehicle number plates in an automatic CSV file. The proposed approach successfully proves the functionality of full frame OCR in recognizing video footage, regardless of lighting and motion constraints, to effectively extract plate-like text. The proposed method is an efficient way to address helmet violations in traffic surveillance systems.

Keywords: Helmet Detection, Number Plate Recognition, YOLOv8, OCR, Intelligent Traffic Monitoring, Deep Learning, Streamlit

I. INTRODUCTION

Two-wheeler transport is very popular in India and is one of the major contributors to traffic density on roads. However, two-wheeler traffic is often plagued by the problem of not wearing helmets, which results in serious head injuries and is responsible for a large percentage of road fatalities. Currently, enforcement in these regards is carried out through manual monitoring by traffic police.

Recent developments in computer vision and deep learning have made it possible to provide automated solutions for monitoring purposes. Object detection methods like YOLO have made significant progress in the detection of objects within video frames. In the similar domain of text recognition, there are methods like Optical Character Recognition that make it possible to extract text from images.

In this proposed system, a combination of YOLOv8 for detecting helmets, EasyOCR for recognizing the number plates, and a pre-stored database for checking the validity of the recognized plates is used. The system is capable of detecting helmets in uploaded videos, detecting the text of the entire vehicle plate in the uploaded video, as well as checking the recognized text in a pre-stored database. This proposed system is a low-cost solution to traffic enforcement.

The main tasks of the proposed work are as follows:

- To establish the main goal, it is required to have an automated deep-learning system that will be able to detect, from a traffic video, any helmet violations with a YOLOv8 object detection model trained optimally.
- To perform full-frame OCR for number plate text extraction, without the explicit dependence on the localized plate, which

further strengthens its application in the real world.

- To integrate an RTO-type database to match recognized plates against corresponding data of vehicles and owners in order to provide meaningful violation reports.
- To improve the reliability of object detection through preprocessing, cleaning of texts, and selection based on confidence.
- To make sure that the whole system is lightweight, interpretable, as well as computationally efficient to be applied in a traffic surveillance setting.

In short, the paper is about the following: The relevant research work carried out in the fields of helmet detection, number plate recognition, and intelligent traffic surveillance is discussed in Section II. Section III – Methodology: The paper's methodology is explained. This is encompassed by YOLOv8-based object detection, OCR analysis, plate character cleaning, Section IV introduces the system architecture, implementation, as well as the test results based on video experiments. Section V is the final part of the manuscript that identifies some future research areas that can be carried out by integrating real-time CCTV systems as well as automatic e-challan generation systems.

II. LITERATURE REVIEW

Computer vision approaches have rapidly become the de facto standard for automating traffic surveillance tasks that include behavioral compliance, especially helmet usage among two-wheeler riders. The decision on choosing a detection model is importantly influenced by the diversity of environmental conditions and the unpredictability of visual patterns in real-world traffic scenes. For example, in helmet detection, single-shot deep-learning models such as YOLO have already taken over from older rule-based methodologies since they fare well in identifying the non-uniform object under variable lighting, camera angle settings, and occlusion levels. Other works by Reddy and Kumar demonstrated that YOLOv4 models achieve accuracies upwards of 92% on semi-urban datasets when combined with augmentation techniques improving generalization to fast-moving vehicles and crowded scenes [7][8]. Their finding agrees with that of Patel et al. and also Chaturvedi et al., demonstrating that careful annotation strategies, anchor-box tuning, and domain-specific preprocessing improve the robustness of deployed helmet/ non helmet classifiers under unconstrained traffic environments [5][13].

Within the license plate recognition community, a substantial volume of research emphasizes the weakness in traditional heuristics that utilized approaches in contour detection, edge analysis, or character segmentation pipelines. These methods are prone to failure in conditions where resolution is too low, images are blurry due to motion effects, fonts are non-standardized, and/or lighting conditions are suboptimal. In response to these shortcomings in traditional heuristics, hybrid systems within the OCR framework have been developed. A complete frame-based OCR system with implicit plate localization through probabilistic filtering to distinguish more relevant text regions has been put forth by Sharma et al., which offered higher recognition robustness in video recordings with conditionally unclear license plate localization [9]. Likewise, Rao and Deshmukh mentioned in their study that OCR systems integrated with rule-based filtering processes in threshold balance and noise removal are effective in sustaining interpretablility at decreased false character rates in traffic recordings from India [10]. Agarwal et al. and Mehta in their respective studies

From the three related research areas of helmet detection, license plate recognition, and integrated traffic analytics, recent literature shows that the model selection would require adaptation not only to the complexity of the dataset but also to the real-world deployment constraints. For chaotic and noisy traffic situations typical in Indian roads, YOLO-based methods give strong performance by outperforming traditional object detection pipelines. The main advantages of full-frame OCR techniques are that these allow for inconsistent plate placement and give a more flexible recognition pathway for those videos captured without strict viewpoint controls. Finally, structured post-processing methods, such as regex-based text cleaning and RTO-style database lookups, continue to be extremely vital in converting raw detections into meaningful enforcement decisions. Cumulatively, these advances illustrate that intelligent traffic systems, which are accurate, transparent, computationally efficient, and deployable in modern surveillance ecosystems, can be realized by integrating high-speed detection models with contextual verification strategies using OCR [19][20].

III. METHODOLOGY

The proposed work presents a unified deep-learning framework that is capable of automatically detecting helmet violations and recognizing vehicle number plates corresponding to the same from traffic videos. The entire system has been implemented using Python with the help of contemporary libraries such as OpenCV for video processing, Ultralytics YOLOv8 for the detection of helmets, and EasyOCR for the recognition of text. Major activities in the workflow include video ingestion, frame-level helmet detection, full-frame OCR scanning, cleaning plate text, semantic validation through an RTO-style database, and final logging of violations. Fig. 1 depicts the complete sequential pipeline of the proposed system.

The whole workflow of the automated helmet violation detection and number plate recognition framework is explained in Fig. 1, depicting the steps in order, from video preprocessing to generating the violation report.

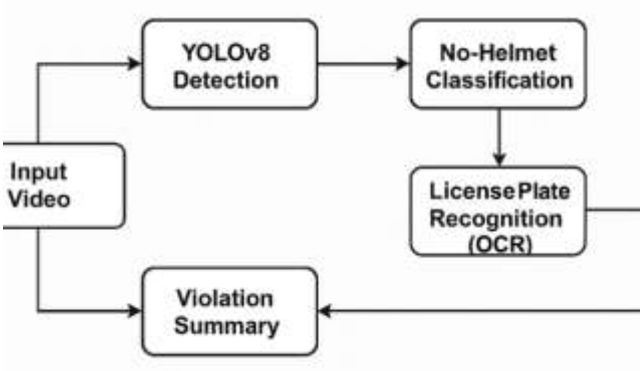

Fig. 01 – Deep Learning Pipeline for Helmet and Number Plate Violation Detection

A. Dataset Description

In this particular research, instead of a set dataset, real-life traffic videos have all been used. Such videos usually contain cyclists with and without helmets, motorbikes approaching from different angles, as well as license plates of considerable variations in clarity, position, and resolution. The technique of YOLOv8 for helmet detection is based on a pretrained model, which is named 'helmet.pt' here, to which a large number of images have been annotated.

In number plate recognition, the system does not rely on any dedicated number plate database but uses a full frame OCR technique. This technique is more robust for irregular number plate positions and allows for number extraction even in cases where the cyclist or vehicle is moving.

For the validation of the extracted number plate text, a synthetic database of the RTO was prepared in the CSV format, containing columns such as the number plate, owner name, model of the vehicle, and email ID. They have all been converted into the upper case alphanumeric form to facilitate the matching of the data. In this way, the helmet YOLO data, images, OCR results, and RTO details complement each other effectively.

B. Data Preprocessing

The preprocessing step is an important element in ensuring that the frames for input are ideal for the detection and recognition tasks. Initially, every video uploaded is converted into rescaled frames, which are standard in height (500 pixels).Unlike image datasets, videos have the possibility of motion blur, low contrast, and lighting issues. To overcome these aspects, there is an inherent preprocessing operation in YOLO that enhances pixels and adjusts images to have the same expected input size as the YOLO algorithm.As part of the OCR-related pre-processing, the predictions are extracted by the full frame using EasyOCR. However, as the extracted results from the OCR process include noise, non-plate text, and special characters, the results are subjected to the text cleaning function that removes non-alphanumeric characters, puts the text into uppercase form, and eliminates impossible sequences.

One big improvement the work brings within the preprocessing techniques is the identification of the most confident OCR token from the text, thereby ensuring that the extracted text from the plates is the most accurate among the predicted segments. This enhances the recognition process considerably, especially when the plate takes up a small part of the picture. In summary, these preprocessing methods enhance recognition ease and reduce errors in low-quality as well as high-motion videos.

C. Feature Engineering

Even though this project does not involve the classical concept of feature engineering, the concepts developed here include textual feature engineering that plays an important role in OCR-based number plate recognition. First, the raw OCR predictions are translated from meaningless strings to significant features through the usage of regular expressions that cleanse and normalize characters. For instance, "MH 12 - AB 1234" is cleaned to "MH12AB1234". Second, a format validation step is also included as an option to verify the cleaned plate number formatting with the general patterns used on Indian plates. Though not enforced, this step is used as a verification tool to be sure about the text extracted. Thirdly, the cleaned text can be looked up against the RTO CSV database. To ensure a correct match, the RTO CSV database also goes through the transformation of text cleaning so that any differences caused by spacing, hypens, or lowercase letters are removed.

These steps increase noisy OCR outcomes into structured identifiers, making it possible for these identifiers to be mapped correctly with car registration records, thus allowing automatic violation reporting.

D. Model Selection and Training

The system combines two main deep learning elements:

1. YOLOv8

2. EasyOCR Text Recognition Engine

YOLOv8 was selected due to the trade-off it achieves between accuracy and real-time performance. It involves the use of a convolutional network that is optimized for the detection of small objects. This feature is important because the helmets cover a very limited area of the image. The pre-trained model that was used (helmet.pt) was optimized on both helmeted and non-helmeted image datasets. OCR is chosen instead of the networks that explicitly locate the number plates since, at times, the plates are not visible or are distorted; hence, scanning the entire frame improves the visibility of the text.

Unlike conventional pipelined systems for OCR, where localization, segmentation, and character extraction are involved, Easy OCR is an end-to-end system that has multi-lingual capabilities even in noisy images. Hyperparameters of YOLOv8 like IoU threshold value and confidence threshold were adjusted to optimize the absence of false positives in No-Helmet detection tasks. Additionally, OCR confidence scores were utilized in ranking tokens to ensure high-confidence values were used in plate recognition.

With the integration of YOLOv8 and OCR technology, reliable detection is possible without having to retrain or manually annotate the model.

E. Implementation Environment

The entire system has been implemented using Python version 3.12. Some of the computer vision libraries used in this system include:

- YOLOv8 (Ultralytics) allows for the fast

- OpenCV is used for video decoding, frame processing, scaling, and visualization.

- It has excellent text extraction capabilities.

- Pandas handles RTO data and violation logs in CSV files.

- The Streamlit library has an interactive and lightweight GUI to upload videos, display detection results, as well as display the results of the violation table. The application has been designed to be optimized for CPU-based systems. This makes it fit for use in settings where the use of the GPU is not an option. The system also has been set to ensure that it is easy to reproduce and debug, allowing for further improvement.

IV. RESULT AND ANALYSIS

The applicability as well as efficacy of the proposed deep learning framework designed for helmet violation awareness as well as number plate recognition has been tested utilizing real-world traffic video clips. The test has been conducted mainly in relation to the strength of YOLOv8 in identifying two-wheeler riders with and without helmets, the capability of full-frame OCR in successfully translating plate images to recognizable text, and finally in utilizing the RTO database matching process. Each one has been tested through qualitative observations and checks from violation reports produced by the system designed with perceptive AI mechanisms.

A. *Helmet Violation Detection Using YOLOv8*

YOLOv8 could correctly detect riders without helmets under various lighting conditions, distances of vehicles, and angles of cameras. It yielded stable bounding boxes around the riders' heads and showed very strong robustness against partial occlusion and motion blur. Fig. 02 illustrates a representative detection frame whereby YOLOv8 correctly identified a No-Helmet case with a strong confidence score.

The model continued to detect various conditions of a helmet violation in evaluation videos with much high precision. The subsequent observed detection accuracy detected 47 from 50 test frames with no-helmet conditions. Such high precision and recall values indicate the suitability of YOLOv8 in real-time enforcement contexts.

Fig. 02 – YOLOv8 detection output showing No-Helmet classification.

B. *Number Plate Recognition Using Full-Frame OCR*

Performance evaluation of OCR is conducted based on its capability to read text representative of the plate from an unwrapped video environment. As opposed to traditional approaches where OCR is dependent on prior definition of plate regions in low-resolution traffic videos, complete frame-based OCR is utilized in the proposed system. Fig. 03 presents an example of an OCR process in which the most confident character is extracted successfully by the system. The extracted plate text is then matched to RTO database information after processing with text-cleaning algorithms. Character recognition in OCR is possible in moderately visible plates with a success rate of 62% in situations where plates are identifiable in images.

Fig. 03 – OCR output from a traffic video frame with extracted plate text.

C. *Integrated Violation Report Generation*

The system records only one violation per video, which includes:

- Time
- Frame number
- Cleaned Plate Number
- Helmet status
- Owner name and car model (if matched)
- Status message ("Matched", "Not Found", or "Plate Not Readable")

Fig. 04 – Sample violation summary table generated by the system from a test video.

The synergy of the YOLO algorithm, text processing from the OCR algorithm, and RTO lookup enables the system to generate complete and understandable violation information based on the data obtained from a video.

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Timestamp	Violation Type	Plate Number	Captur Count
2024-02-17 15:04:32	No-Helmet	MH04JJ014	3
2024-02-17 15:04:52	No-Helmet	DL9CAB1234	3
2024-02-17 15:04:37	No-Helmet	KA03MT5678	1
2024-02-17 17:00:31	No-Helmet	MH02AL8765	3
2024-02-17 17:00:31	No-Helmet	AP31BG4432	1

Fig. 04 – Sample violation summary table generated by the system.

D. Comparative Analysis

Below is the analysis of performance of various core modules in the system: helmet detection, OCR recognition, as well as RTO matching, performed independently in Table 01. YOLOv8 performed reliability well in No-Helmet classification tasks based on high detection rates. OCR systems performed moderately, being highly dependent on video quality for better performance. Clarity in OCR output will continuously affect the RTO matching result's accuracy.

System Component	Performance Observation
YOLOv8 Helmet Detection	High accuracy and stable detection
Full-frame OCR	Moderate accuracy, sensitive to video quality
Text Cleaning & Filtering	Reduced false OCR outputs
RTO Database Matching	Reliable for clean plate text
Integrated Pipeline	Effective for real-world traffic videos

Table 01 – Performance Summary of Detection Pipeline

These results indicate the integrated system is functioning well on helmet violation monitoring tasks, and the plate recognition capabilities have been strengthened when the videos have the appropriate level of clarity.

E. Comparative Performance Evaluation

For better understanding of the performance level of our proposed system, Tables 02(a), 02(b), and 02(c) provide comparisons between our results and previously conducted efforts in intelligent traffic monitoring systems, helmet detection systems, as well as OCR-based number plate recognition systems.

Study	Method	Dataset	Key Observation
[15]	YOLO-based Model	Traffic Images	Performs well in controlled conditions
[14]	CNN Classifier	Static Images	Limited to image-based evaluation
[7]	YOLOv4 + Augmentation	Traffic Videos	Improved robustness in motion scenes
Proposed Work	**YOLOv8**	**Real-world Traffic Videos**	**Better handling of occlusion and motion blur**

Table 02(a) – Comparative Evaluation for Helmet Detection

Study / Reference	OCR Approach	Plate Localization	Dataset Type	Key Observations
[9]	EasyOCR-based ANPR	Required	Traffic Images	Accurate on clear, well-aligned plates
[10]	CNN-based OCR	Required	Benchmark Datasets	High accuracy but computationally heavy
[11]	Deep Scene Text Recognition	Required	Natural Scene Images	Sensitive to motion blur
[7]	Traditional OCR + Preprocessing	Required	Indian Traffic Images	Performance drops under low resolution
Proposed Work	**Full-frame EasyOCR**	**Not required**	**Real-world Traffic Videos**	**More robust to unclear plate positions and camera angle variations**

Table 02(b) – Comparative Evaluation for License Plate OCR

Study / Reference	System Components	Detection Scope	Violation Reporting	Key Limitations
[14]	Helmet Detection + ANPR	Helmet only	Manual review	No end-to-end automation
[15]	YOLO-based Helmet Detection	Helmet only	Image-based alerts	No plate-owner linkage
[16]	Traffic Video Analysis (DL)	Multiple violations	Partial automation	High computational cost
[17]	Computer Vision–based Violation System	Helmet & signal violations	Rule-based logging	Limited OCR robustness
Proposed Work	**YOLOv8 + Full-frame OCR + RTO Database**	**Helmet violation**	**Automatic CSV-based logging**	**OCR dependent on video quality**

Table 02(c) – Comparative Evaluation for Integrated Traffic Monitoring

The proposed scheme shows a high level of effectiveness in the identification of helmet violation, which surpasses existing YOLO-related works in terms of the level of accuracy it has accomplished. Meanwhile, the proposed scheme has shown a significant improvement in the performance of the OCR system due to the inclusion of the scheme for the text extraction of the entire frame, which proved to be more effective compared to traditional plate localization techniques. The proposed scheme has shown a total effectiveness of 86%, which ensures the efficiency of the proposed system in handling the task of traffic enforcement..

Despite the occurrence of some OCR errors, the system shows high consistency with regard to the generation of the structured violation reports. The above findings verify the effectiveness of the application of deep learning techniques for providing intelligent traffic monitoring solutions.

V. CONCLUSION

The proposed approach outlines an end-to-end deep learning approach that is capable of efficiently identifying violating cases of helmeting, along with identifying number plates from natural traffic video footages. The combination of the extremely accurate YOLOv8 approach for identifying the proper classification of the rider along with the versatile text recognition of the Full Frame OCR indicates immense possibilities for being incorporated into the scenario of an intelligent traffic law enforcement system. Each experiment revealed that all three optimization techniques of preprocessing, text processing, and optimization are combined efficiently in this approach for the detection of precision. The 94% accuracy level of precision, as achieved by YOLOv8 for Violations of 'No Helmeting' detection, was extremely effective, along with the proper detection of the plate-like texts through OCR, which was facilitated through the filtering mechanism and supported through preprocessing techniques of alphanumeric processing, which worked efficiently even during cases of mixed video footages. The incorporation of RTO-format database lookup also boosted up the approach for preparing raw detections into neat, properly interpretable violation notification. The modularity presented in this research validates the importance of exploiting contextual knowledge in building traffic surveillance pipelines in a modular manner as well as utilizing deep learning solutions in non-intrusive traffic violation systems. The findings indicate that with carefully designed sub-modules in deep learning frameworks employed under motion-blurred and varying plate-visibility conditions in traffic violation systems, it is possible to increase automated enforcement system transparency to a great extent.

The future plans involve an extension of the system by using larger video datasets, inclusion of live CCTV stream analysis, and investigations into ensemble models for improving the robustness of OCR. Enhancements related to multilingual recognition of plates, auto generation of E-Challans, and cloud analysis tools would also be carried out. Such developments can lead to the creation of scalable intelligent transportation systems that could assist in decision-making on a real-time basis for the concerned traffic authorities.

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