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Automated Traffic Violation Detection: Helmets and License Plates

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Abstract:

Road safety is a serious concern in metropolitan areas, with many traffic offenses ascribed to motorcycle riders who do not wear helmets. Manual enforcement of such breaches is labor-intensive and frequently unsuccessful due to the large number of cars. This project proposes a Automated Traffic Violation Detection System that detects helmet violations in real time and identifies violators using powerful deep learning algorithms.

The system uses the YOLO (You Only Look Once) object detection algorithm to accurately and quickly detect motorcycles, riders, and helmets in video feeds or surveillance material. When a rider is spotted without a helmet, the technology activates an automatic pipeline that locates and extracts the vehicle's license plate. The Optical Character Recognition (OCR)module, like Tesseract, is then utilized to read the alphanumeric characters on the license plate and identify perpetrato Captured violations are saved with metadata such as the license number, date, time, and proof image, which can then be incorporated into a database or used to create automated challans (tickets). The suggested method greatly decreases the need for manual monitoring, improves enforcement accuracy, and helps to more compliance with traffic regulations. This technology can be used in smart cities and combined with current traffic management infrastructure to produce a scalable, efficient, and automated traffic law enforcement tool.

Keywords: Convolutional Neural Network (CNN), YOLO (You Only Look Once), Optical Character Recognition (OCR).

INTRODUCTION:

Ensuring road safety has become increasingly difficult in today's fast paced metropolitan areas. Among the several traffic prohibitions, riding without a helmet remains one of the most common and deadly, frequently resulting in serious injuries or fatalities in accidents. Despite awareness campaigns and rules requiring helmet use, compliance remains low in many areas. Traditional methods of monitoring such violations rely mainly on manual observation by traffic personnel or post- incident analysis of CCTV material, both of which are time consuming, resource-intensive, and susceptible to human error. To solve these restrictions, the

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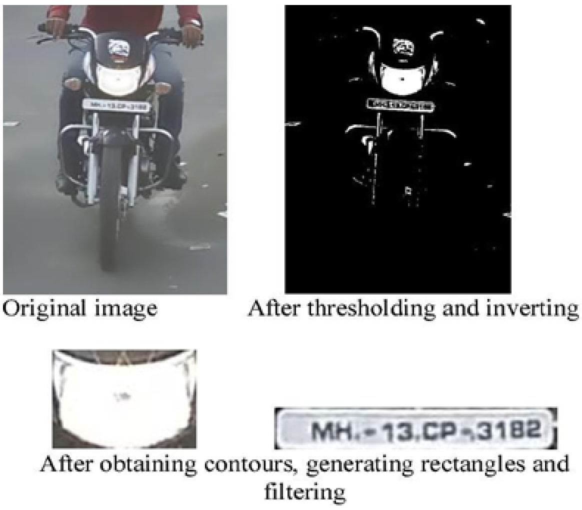
discipline of intelligent traffic management is focusing on automation through computer vision and machine learning. This project provides an Automated Traffic Violation Detection System that detects helmet violations in real time and identifies the violators using their license plate numbers. The system leverages YOLO (You Only Look Once), a cutting-edge deep learning-based object detection algorithm known for its speed and accuracy. It is capable of detecting motorcycles, riders, and helmets in video frames. If a helmet is not detected on a rider, the system proceeds to locate the vehicle's license plate using additional detection models and then applies Optical Character Recognition (OCR) to extract the registration number from the image. By automating the entire pipeline—from violation detection to license plate recognition and data logging—this system offers a robust, scalable solution for modern traffic enforcement. It reduces dependency on manual intervention and allows traffic authorities to monitor violations more efficiently and consistently. The integration of such AI-powered solutions into existing infrastructure can significantly enhance road safety, streamline law enforcement operations, and support the development of smart city ecosystems. Traffic violations, particularly by motorcyclists who do not wear helmets, are a major cause of road accidents. Manual monitoring is inefficient and hard to scale.

This proposal proposes an automated system that leverages YOLO, a real-time object identification algorithm, to detect helmet violations and capture the license plates of violators. By integrating OCR for license plate recognition, the system enables automatic detection, documentation, and reporting of violations, supporting smarter and safer traffic management.



YOLO: You Only Look Once

YOLO is a real-time object recognition technique that examines the entire image at once, making it highly quick and ideal for live video analysis. YOLO, unlike prior object detection systems that scan portions of the image numerous times, employs a single convolutional neural network to predict bounding boxes and class probabilities from entire images. This project uses YOLO (e.g., YOLOv5 or YOLOv8) to detect critical elements such as motorcycles, riders, helmets, and license plates in each video frame. The algorithm's balance of speed and accuracy ensures that even fast-moving vehicles in traffic footage can be accurately analyzed in real time. YOLO's ability to detect multiple objects simultaneously is

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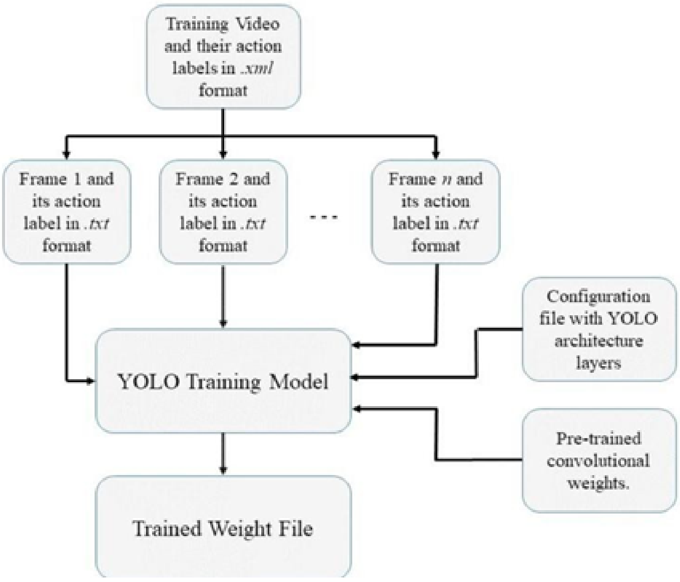
especially useful
here, as the system needs to determine if a helmet is present on a rider while also identifying the vehicle and its license plate. Computer vision is the technology that enables machines to read and comprehend visual information contained in digital images or video frames. I n this project, it is utilized to evaluate raw video feeds, recognize moving objects, and extract key visual features for violation detection purposes. Tasks like background subtraction, motion detection, and region-of-interest cropping are all part of computer vision. Once YOLO detects the rider and the bike, computer vision techniques help track these objects, isolate the helmet region (or lack thereof), and crop the license plate area for further analysis. Without computer vision, the system would not be able to interpret camera feeds or understand where to apply detection or OCR. It forms the foundation upon which all visual tasks in the project are built.



OpenCV

OpenCV is a powerful, open-source library in Python and C++ that supports a wide range of computer vision tasks. In this project, OpenCV receives video input from surveillance footage, processes individual frames, and supports picture operations such as scaling, blurring, edge detection, and contour finding. It also supports drawing bounding boxes around detected objects, displaying the processed video with annotations (e.g., “Helmet Detected” or “No Helmet”), and saving images of violations. OpenCV is also responsible for isolating the region of interest (like cropping the license plate area) before feeding it into the OCR module. Its flexibility and large community support make it a central part of the project’s image handling pipeline.

Python

Python is the main programming language used in this project due to its ease of use and the vast ecosystem of libraries and frameworks for machine learning, computer vision, and automation. Libraries like OpenCV, PyTorch (for running YOLO models), and Pytesseract

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(for OCR) are all accessible and well supported in Python. The entire pipeline—video capture, detection, decision- making, OCR processing, logging, and saving evidence—is implemented using Python scripts. Its readability and integration capabilities allow developers to quickly prototype, debug, and scale the system. Moreover, Python supports integrating the detection system with back-end databases or APIs for tasks like e-challan generation and violation reporting.

DATA SET PREPARATION

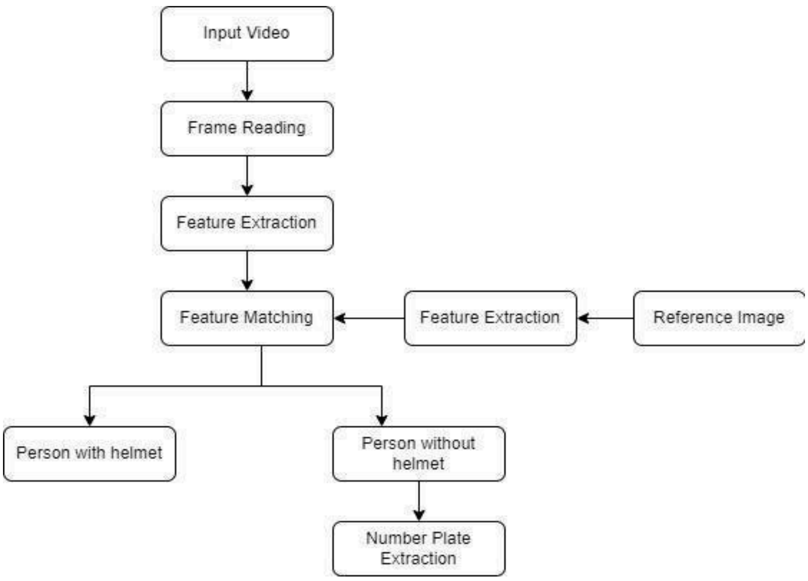
The success of any machine learning model depends on the quality and quantity of the data it is trained on. For this project, dataset preparation involves collecting images of motorcyclists (with and without helmets), different types of motorcycles, and clearly visible license plates from various angles and lighting conditions. These images need to be annotated using tools like LabelImg or Roboflow, where bounding boxes are manually drawn around the objects of interest (helmet, head, bike, plate). The dataset should have sufficient diversity—different helmet types, rider positions, and vehicle designs—to generalize well during real-world testing. The prepared dataset is then used to train or fine tune the YOLO model to recognize these objects in real-world scenarios with high accuracy.

METHODOLOGIES:

1. Computer Vision & Deep Learning: Uses Convolutional Neural Networks (CNNs) for helmet detection in images/videos from traffic surveillance cameras. Implements YOLO (You Only Look Once) for real-time object detection to identify motorcyclists without helmets.
2. Optical Character Recognition (OCR): Extracts alphanumeric characters from number plates using OCR based image processing techniques. Prepossessing steps like noise reduction, contrast adjustments, and segmentation improve OCR accuracy.
3. Implementation Tools:
    - Programming: Python 3.10
    - Development Environment: VS Code
    - Frameworks/Libraries: Ultralytics YOLOv5, Roboflow (data augmentation), Tesseract/Keras OCR/EasyOCR
4. Image Pre-processing:
    - Re-sizing, normalizing pixel values, and converting image formats (e.g., BGR to RGB) for better model accuracy.
    - Bounding Box Regression:
    - Predicts object locations (rider, helmet) within an image by drawing bounding boxes.
    - Intersection Over Union (IOU):
    - Ensures accurate bounding box placement by eliminating overlapping or

incorrect detection's.

5. Multi-Step Detection Approach
    - Step 1: Detect the presence of a person using YOLO-V5.
    - Step 2: Identify the motorcycle/moped.
    - Step 3: Check if the detected person is wearing a helmet using a dedicated YOLO-V5 helmet detection model.
6. Predefined Constraints and Conditions
    - Ensuring accuracy in license plate extraction.
    - Processing video inputs efficiently in real-time.
    - These methodologies aim to automate the detection of helmet violations and extract license plate numbers for enforcement.



LITERATURE SURVEY:

Automated traffic violation detection systems have received a lot of interest in recent years because of their ability to increase road safety and effectively enforce traffic regulations. These systems use advanced computer vision and machine learning to detect and record breaches, such as helmetless riders and unregistered vehicles, in real time. However, present methods have hurdles in terms of accuracy in a variety of situations, scalability, and interface with enforcement systems. Image processing and machine learning techniques are crucial for detecting traffic violations.

Deep learning models such as CNNs have shown promise in recognizing helmets, although they frequently struggle with occlusions and changing lighting conditions. Similarly, OCR-based algorithms for license plate recognition encounter difficulties such as motion blur, low resolution photos, and non standard license plate formats. Traditional traffic monitoring systems usually lack real-time data Processing causes delays in enforcement and affects overall efficiency. Many of these technologies run independently, without being integrated into smart city frameworks or complete traffic management systems, which limits their utility.

The proposed project, Automated Traffic Violation Detection: Helmets and License Plates, seeks to address these issues by using powerful machine learning models like YOLO for object detection. This ensures accurate identification of helmetless riders and improves license plate recognition using OCR techniques, even in challenging conditions. Furthermore, the system incorporates cloud-based analytics for real- time processing, enabling rapid notifications to offenders and seamless connection with law enforcement databases. By leveraging IoT- enabled smart cameras, the system ensures scalability and efficient deployment across diverse settings.

Adaptive algorithms adjust detection thresholds based on environmental factors like lighting and weather, enhancing robustness. This solution combines real-time detection, seamless integration, and analytics to create a scalable, efficient, and transformative traffic monitoring system. By addressing existing gaps, the project promotes road safety and compliance while contributing to a modern and effective traffic management ecosystem.

Key features:

- Real-Time Helmet Detection Automatically determines whether a motorcycle rider is wearing a helmet or not. YOLO is used to accurately and quickly identify objects in video streams.
- License plate detection Detects and crops the violating vehicle's license plate. Works in real time with helmet detection.
- License Plate Recognition (OCR) The license number is extracted from the plate using optical character recognition (OCR). Converts image- based text to a legible and searchable format.
- Deep Learning for Object Detection. Uses YOLOv5 or YOLOv8 to detect multiple objects (motorcycle, rider, helmet, and license plate). Capable of processing several frames per second from live feeds. Violation Logging & Evidence Storage Stores violation details such as: Cropped image of the violation License, number Date and time Option to export logs for reporting or database.

    - Video frame processing for CCTV, IP cameras, and stored footage.
    - Analyzes frame every frame to ensure that no violations are overlooked.

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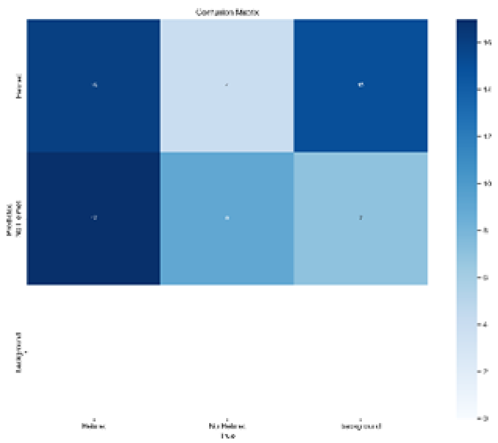
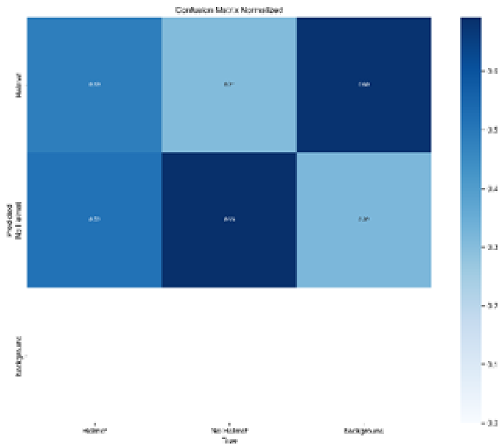
- Automated, unattended operation Runs constantly without human intervention. Ideal for 24/7 traffic surveillance and monitoring.
- Scalable and deployable. Can be deployed at traffic signals, highways, or integrated into smart city systems. Easily scalable to multiple locations and camera feeds.
- Visual Alerts and Annotations Annotates video frames with bounding boxes and labels (e.g., "No Helmet Detected"). Useful for both real-time monitoring and video playback.
- Modular Architecture Each module (detection, OCR, logging) is independent and customizable. Easy to update or improve individual components.

EVALUATION METRICS & ANALYSIS

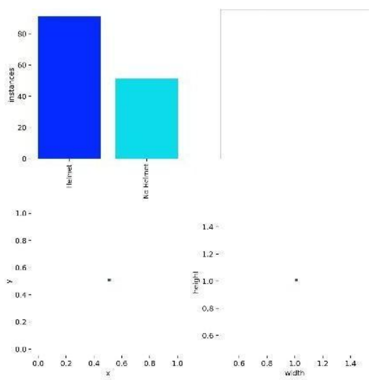
Analysis: Model - 1:

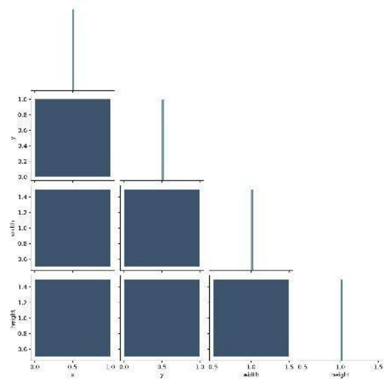
Confusion Matrix:





Labels:





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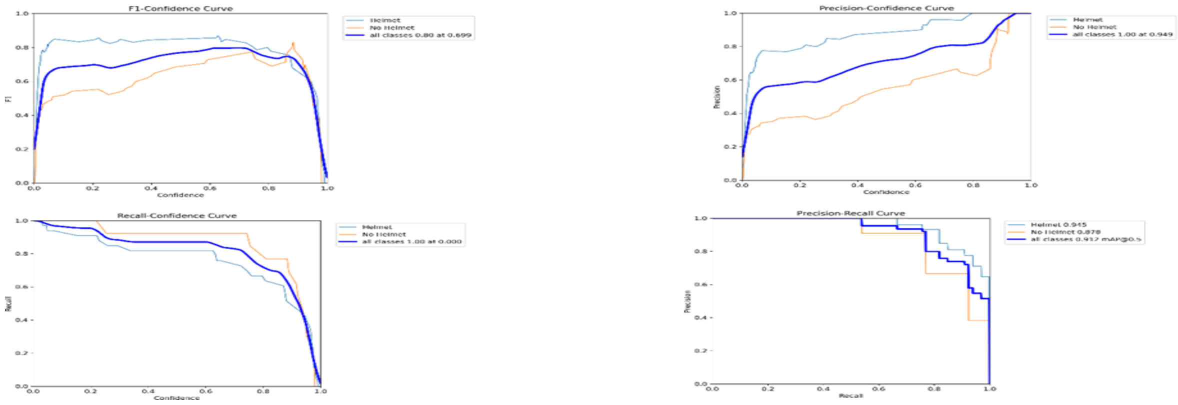
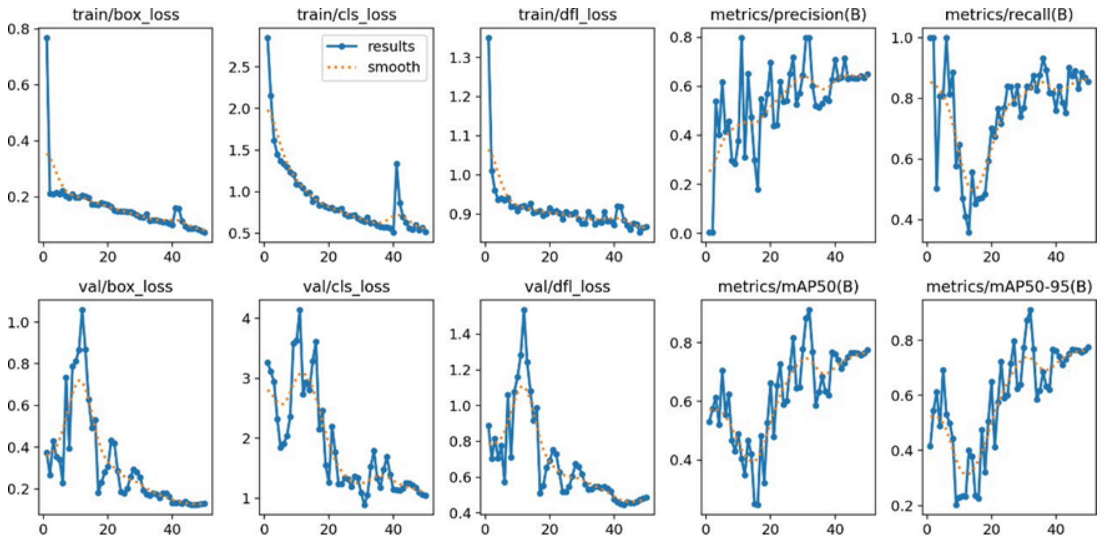
Curves :



Results:



The training graphs suggest that the model has successfully converged. The training and validation losses (box, classification, DFL) fell steadily throughout epochs, indicating that the model learnt efficiently. Precision, recall, and mAP metrics all increased, with mAP50 reaching approximately 0.8, indicating trustworthy object detection ability. The confidence curve graphs indicate optimal detection performance at the 0.7 confidence threshold, with the greatest F1 score (~0.80). The precision-recall trade-off is fairly balanced. Helmet detection outperformed no-helmet in terms of precision and recall, indicating that the model is more confident and accurate in identifying helmets. Overall, the model trained with YOLO is well-suited to the task of detecting traffic offenses involving helmets. The results indicate that it may be confidently implemented in real-time circumstances, with good accuracy in identifying helmet usage.

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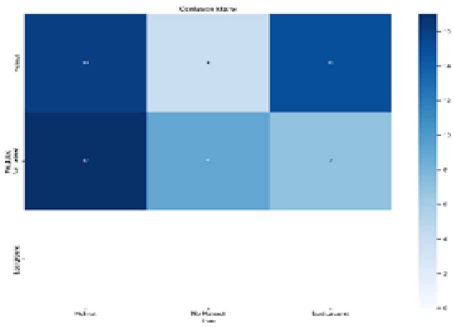
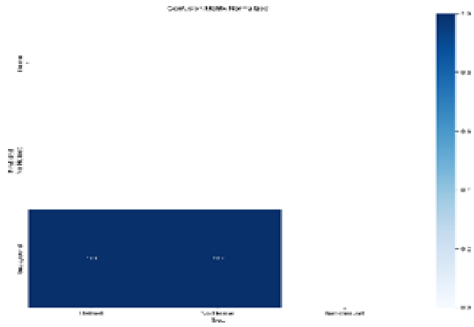
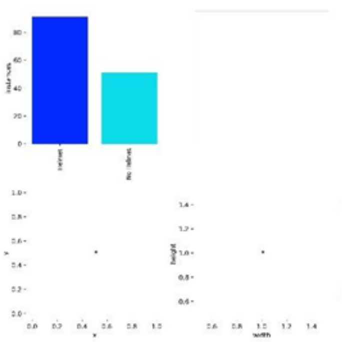
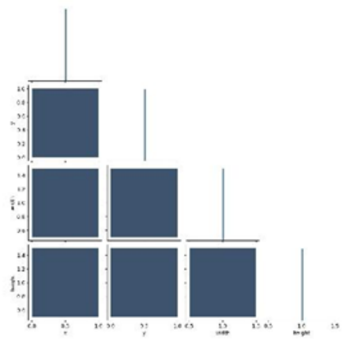
Model - 2:
Confusion Matrix:



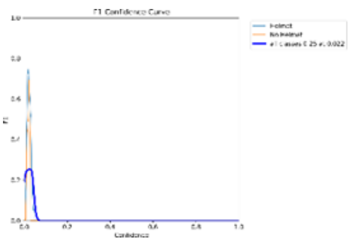


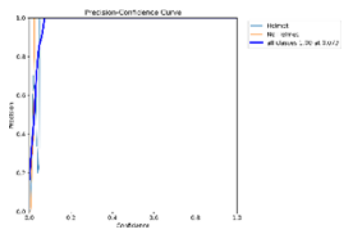
Labels:

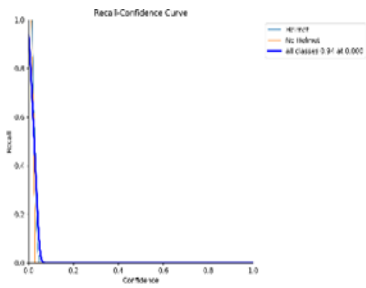


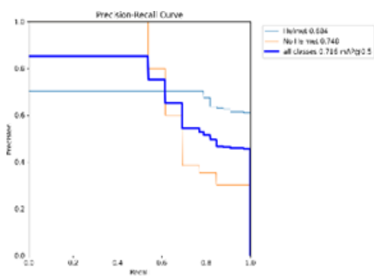


Curves :









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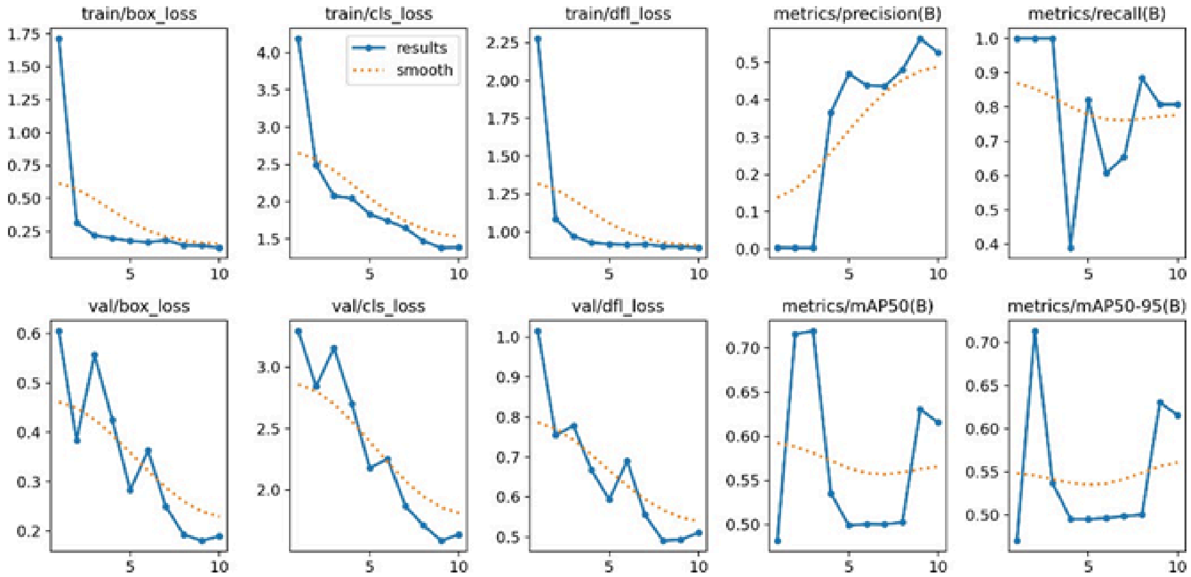
Results:



Model 2 performed well throughout training, as seen by a consistent decrease in training and validation losses across the box, classification, and distribution focal loss (DFL) measures. By the tenth epoch, these losses had essentially stabilized, showing that the model had successfully learned the data's underlying patterns. The precision confidence curve demonstrates that the model achieves a precision of 1.00 at a relatively low confidence threshold (0.073), implying extremely confident and accurate predictions for both the "Helmet" and "No Helmet" categories. Furthermore, the normalized confusion matrix shows flawless categorization, with no misclassifications between categories. The precision, recall, and mean Average Precision (mAP) metrics particularly mAP@0.5 and mAP@0.5:0.95 remain consistently high, confirming the model’s robustness and reliability in object detection tasks. Overall, Model 2 demonstrates good training behavior and prediction accuracy, making it a suitable candidate for real-time safety monitoring applications.

Key features:

- Convergence: Highlight the decreasing loss values over epochs, showing the model is learning.
- Generalization: Emphasize the similar trends in training and validation, indicating good generalization.
- Performance Metrics: Focus on the improvement in precision, recall, and mAP, demonstrating the model's effectiveness in object detection.
- Smoothing: Mention the use of smoothing to better visualize trends and reduce the impact of noise. Remember to tailor the paragraph to the specific context of your paper and the broader discussion of your methodology and results.

Real time dataset collection:

To build an effective and realistic detection model, the dataset for this project was collected manually in real-time environments. Instead of relying on pre-existing or synthetic data, images were captured directly at traffic signals, road junctions, and busy streets using mobile phone cameras. This approach allowed for the inclusion of various real-world conditions such as different lighting (morning, afternoon, evening), diverse backgrounds, multiple rider positions, and a wide range of motorcycle types. Special care was taken to capture images that clearly show motorcyclists both wearing and not wearing helmets, along with the corresponding license plates when visible. The manually captured images offer the advantage of being highly relevant and context-specific, as they reflect the actual scenarios the system is expected to handle. After collecting the In the photographs, annotation tools such as Label Image were used to put bounding boxes around things of interest, such as riders, helmets, motorcycles, and license plates. This manually annotated dataset serves as the YOLO model's training input, allowing it to learn object attributes under real-world traffic conditions. The diversity and authenticity of the dataset significantly improved the model’s robustness, making it better suited for deployment in practical urban environments.

Conclusion

After image collection, the dataset was thoroughly inspected and separated to ensure quality and consistency. Images were first categorized as "Helmet" or "No Helmet" based on whether the cyclist was wearing a helmet. Further segmentation was performed based on license plate visibility; only photos with clearly visible and readable plates were included in the OCR training. During this process, any images that were heavily blurred, overexposed, underexposed, or partially obstructed were either discarded or moved to a separate validation set to test the model’s robustness. Special attention was given to maintaining a balanced dataset, ensuring equal representation of various classes (helmet/no helmet, readable/unreadable plates). To ensure uniformity, images were scaled and normalized during preprocessing. During training. This segregation helped improve model accuracy and minimized the risk of poor predictions due to low-quality or irrelevant data.

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