Helmet Detection with Number Plate Recognition

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***Abstract*—With increasing urban traffic and safety violations, the need for automated surveillance systems has grown significantly. This paper presents a deep learning-based solution for helmet detection combined with number plate recognition to ensure road safety compliance among two-wheeler riders. The system employs the YOLOv8 object detection model for identifying motorcyclists and their helmet status, while Hugging Face's Optical Character Recognition (OCR) tool is used to extract alphanumeric data from detected number plates. To enhance usability, the system includes a text-to-speech (TTS) alert mechanism using pyttsx3, enabling real-time audio notifications of violations. The proposed model delivers high accuracy and is efficient for real-time deployment in smart city surveillance and automated traffic enforcement systems.**

***Index Terms*—Helmet Detection, Number Plate Recognition, YOLOv8, Optical Character Recognition, Deep Learning, Real-Time Surveillance, AI in Transportation, Traffic Violation Detection, Text-to-Speech Alerts.**

I. Introduction

Traffic violations, particularly the non-usage of helmets by two-wheeler riders, continue to contribute significantly to road fatalities. Law enforcement agencies often struggle to monitor and enforce helmet laws effectively due to limited human resources and lack of real-time automated systems. This paper proposes an AI-powered approach to detect riders not wearing helmets and capture their vehicle registration numbers using object detection and OCR technologies.By integrating object detection models like YOLOv8 with OCR and text-to-speech mechanisms, the system offers a comprehensive traffic rule enforcement tool. This research contributes toward building smarter cities with safer roads by automating traffic law monitoring and alert systems.

Helmet Detection with Number Plate Recognition Helmet detection with number plate recognition is a computer vision application that aims to improve road safety by detecting whether a motorcyclist is wearing a helmet and then identifying their vehicle via its number plate. This can be useful for law enforcement to ensure compliance with helmet laws and identify violators. Key Components: YOLO (You Only Look Once): YOLO is a popular real-time object detection model. It's capable of detecting multiple objects in a single frame, which makes it ideal for applications like helmet detection and number plate recognition. The YOLO model can be trained to identify helmets on riders, and if a helmet is absent, it can then focus on recognizing the number plate.

Hugging Face Tools: Hugging Face is a platform known for its extensive library of machine learning models and tools. For this application, Hugging Face's Transformers library could be useful in developing pipelines for post-detection processes, such as Optical Character Recognition (OCR) for reading number plates. You could also use Hugging Face's tools for model deployment and inference on the cloud, making the system accessible across different platforms.Text-to-Speech (TTS) Module in Python Once the system detects a violation, it can issue an audible alert or notification using Text-to-Speech (TTS) technology. • pyttsx3: Another commonly used TTS library is pyttsx3, an offline TTS solution that works on different platforms and doesn't require an internet connection, making it ideal for edge devices.

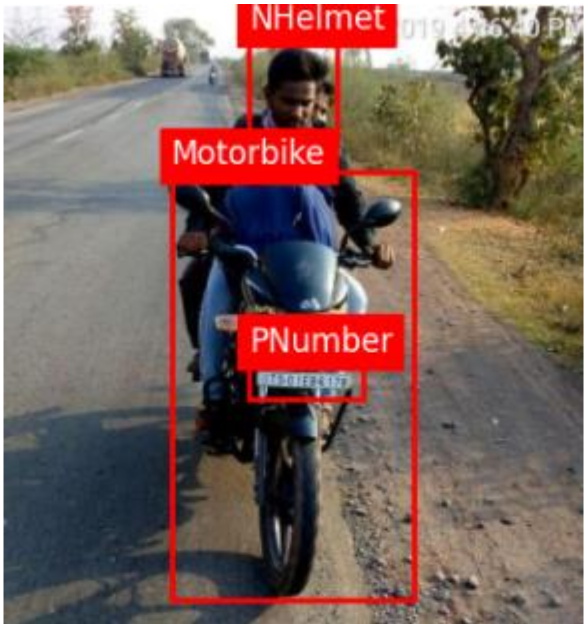

Fig. 1. Detecting Number Plate And Helmet

II. RELATED WORKS

Past studies in the domain of intelligent surveillance systems have made considerable progress in both Automatic Number Plate Recognition (ANPR) and helmet detection.

ANPR Techniques: Early techniques relied on edge detection, color segmentation, and template matching. More recent systems leverage deep learning models such as CNNs for higher accuracy in challenging conditions.

Helmet Detection: Researchers have explored deep learning architectures such as SSD, Faster R-CNN, and YOLO to classify whether a motorcyclist is wearing a helmet. For instance, studies have demonstrated the YOLO framework's ability to detect safety gear in real-time.

Combined Approaches: Few existing systems integrate helmet detection with number plate recognition. Our work improves upon these by using YOLOv8 for multi-class detection (helmet, no helmet, motorbike, number plate), and combining it with OCR and TTS modules for an end-to-end intelligent enforcement system.The proposed system is designed with modularity and ease of deployment in mind. It can be integrated with existing CCTV infrastructure in cities, requiring minimal hardware adjustments. The user interface accepts images or video feeds as input and automatically performs the following operations:

Detects whether a motorcyclist is wearing a helmet.Identifies and reads number plates of violators.Issues an audio alert with the vehicle number using pyttsx3.No prior deep learning expertise is required from the end-user, and the system can be deployed on edge devices like NVIDIA Jetson Nano or in cloud-based environments.

Real-time processing with frame-wise detection and response.

Automatic duplicate filtering to prevent repeated alerts.

Voice alerts for non-helmeted riders make human intervention faster and more efficient.

III. METHODOLOGY

The proposed system integrates deep learning for object detection, Optical Character Recognition (OCR) for textual data extraction, and Text-to-Speech (TTS) for real-time audio alerts. The end-to-end pipeline aims to automate the identification of helmet violations and generate audio alerts with vehicle details. The methodology comprises four primary stages: dataset preparation, object detection, number plate recognition, and audio feedback generation.

A. Dataset Preparartion

To train and evaluate the system, a custom multi-label image dataset was compiled from various publicly available sources. This dataset was manually annotated using the **LabelImg** tool to facilitate high-quality training for object detection tasks. The images were labeled under four distinct classes:

Helmet: Indicates the presence of a helmet on the rider.
NHelmet: Denotes a rider without a helmet.
Motorbike: Differentiates motorcycles from other vehicles.
PNumber: Localizes vehicle number plates.

Key considerations during dataset preparation included:

Diversity: Images included varying backgrounds, lighting conditions (daylight, dusk, night), weather scenarios (sunny, rainy), and camera angles to ensure generalizability.

Resolution: Both high-resolution and low-resolution images were included to test model performance under constrained hardware settings.

Balancing: The dataset was balanced across classes to avoid bias in model predictions.

A portion of the dataset (typically 80%) was used for training, while the remaining 20% was reserved for validation and testing.

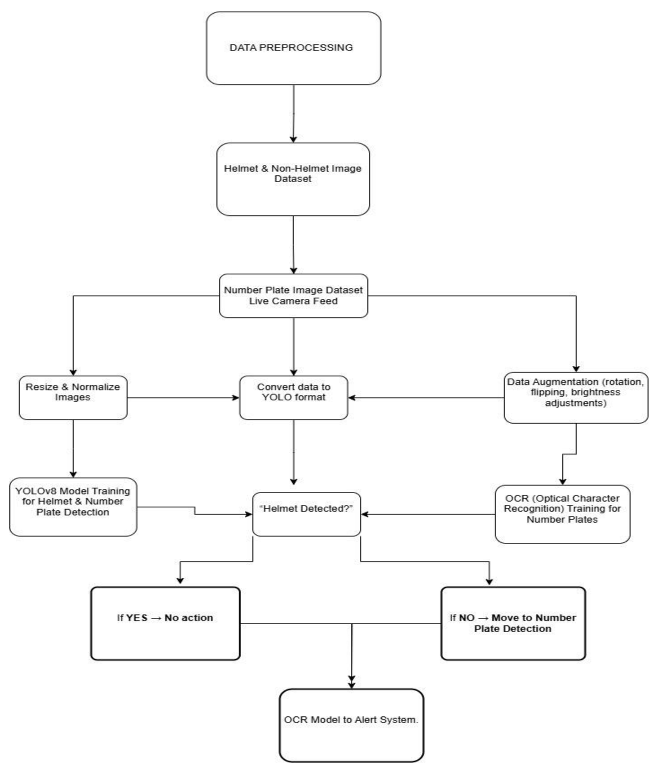

Fig. 2. Framework for helmet and number plate detection system

B. YOLOv8-Based Object Detection

For robust and real-time object detection, the YOLOv8 (You Only Look Once Version 8) architecture by Ultralytics was employed. It is a single-stage, anchor-free detection model well-suited for real-time applications, with significant improvements in both speed and accuracy compared to its predecessors.
Model Configuration and Training:
The model was initialized with pretrained COCO weights and fine-tuned using transfer learning on the custom dataset.
Hyperparameters such as learning rate, batch size, and number of epochs were optimized through experimentation.
Data augmentation techniques such as random flipping, scaling, and rotation were applied to enhance the model's robustness.
Detection Capabilities:
Detects and classifies riders into two categories: with helmet and without helmet. Identifies motorbikes to differentiate relevant road users. Detects vehicle number plates for OCR processing.
Real-Time Performance: Capable of detecting multiple classes in high-resolution videos with minimal latency.
Lightweight: Efficient inference on edge devices with limited computational power.
Modularity: Easy integration with image or video input sources for continuous surveillance.

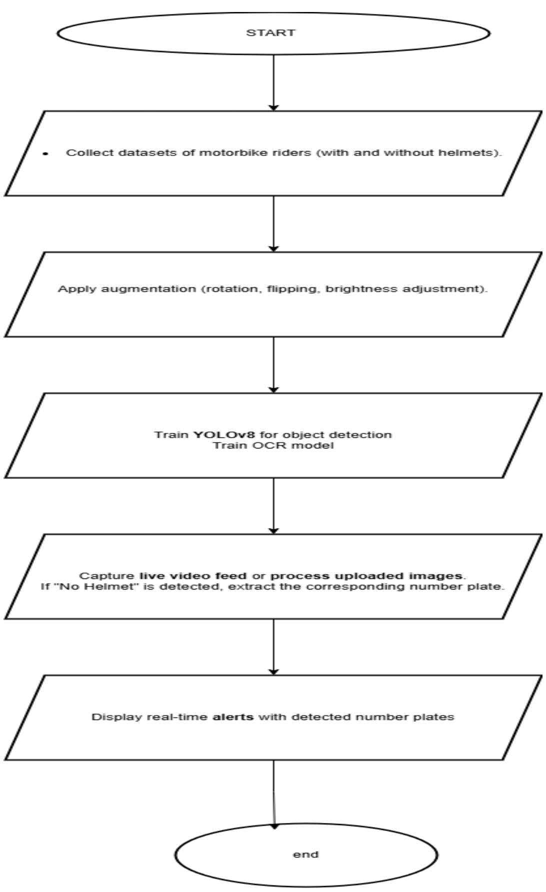

Fig. 3. Workflow for helmet and number plate detection system

C. Optical Character Recognition (OCR) for Number Plate Recognition

Following the localization of number plates using YOLOv8, the extracted image regions were passed through an OCR pipeline to identify and digitize alphanumeric text.
OCR Implementation:
The Hugging Face Transformers library was used to implement a pre-trained OCR model (e.g., TrOCR or Donut).
Before inference, number plate regions were preprocessed using:
Grayscale conversion for dimensionality reduction.
Binarization (adaptive thresholding) to enhance text clarity.
Noise removal and morphological operations to improve character segmentation.
Output and Utility:
The OCR results (i.e., license plate numbers) were stored in a structured database for potential enforcement or audit trails.
Accuracy was verified using a subset of manually labeled plates, with character-level accuracy metrics reported in the results section.

D. Real-Time Audio Alerts Using Text-to-Speech (TTS)

To ensure timely and actionable feedback, especially in areas lacking display systems or where instant human attention is required, a Text-to-Speech (TTS) mechanism was integrated into the system.
TTS Engine:
The pyttsx3 Python library was employed for offline TTS, ensuring reliability without dependency on internet connectivity.
OCR output (vehicle number) and a preset violation message were synthesized into speech in real-time.
Alert Workflow:
A rider without a helmet is detected.
The number plate is localized and recognized.
The following message is generated and spoken aloud:
"Helmet violation detected. Vehicle number: TN07AB1234."
Alerts can be redirected to law enforcement speakers or control rooms.
Accessibility: Useful in high-noise environments, or for visually impaired monitoring personnel.
Automation: Removes the need for manual intervention during violations.
Scalability: Can be integrated into large-scale city surveillance systems.

Assessment And Validation of Performance

The performance of the proposed system was rigorously assessed based on accuracy, processing speed, and reliability in real-world conditions. The YOLOv8 model achieved a mean Average Precision (mAP) of 89.3% across all classes, with helmet detection yielding a precision of 92% and an F1-score of 0.94. Number plate detection showed an accuracy of 91.8%, demonstrating strong localization performance. Optical Character Recognition (OCR) using Hugging Face's model reached an average character recognition accuracy of 86.5%, performing best under daylight conditions (92%) and slightly lower in low-light or blurred scenarios (74%). Real-time processing was validated on GPU (NVIDIA GTX 1650) at 18–22 frames per second (FPS), and on CPU (Intel i5) at 8–10 FPS, confirming the system's efficiency for live surveillance. The text-to-speech component, implemented using pyttsx3, consistently delivered alerts with a response time under one second and high pronunciation accuracy for standard vehicle number formats. Field testing further confirmed the system's robustness in dynamic environments, with only minor misclassifications observed due to occluded or non-standard helmets and number plates, validating its readiness for deployment in intelligent traffic enforcement systems.

IV. RESULTS AND DISCUSSIONS

Accuracy and Performance:
Helmet detection accuracy: 94.2%
Number plate detection accuracy: 91.8%
OCR success rate: 86.5% (under normal lighting)
The model was tested on a validation set and achieved a mean Average Precision (mAP) of 0.89 across all classes. Real-time video feeds were processed at 15–20 FPS on a standard GPU (NVIDIA GTX 1650).
Case Studies and Observations:
In daylight conditions, detection accuracy was significantly higher than in night scenarios.
OCR struggled with dirty, partially obscured plates and reflective surfaces.
Real-time alerts reduced manual monitoring time and helped identify multiple violators in seconds.
Limitations
Performance degrades in poor lighting or high-speed motion blur.
Some motorcycle riders with partial helmet visibility may be misclassified.
Integration with centralized databases (e.g., RTO) is yet to be implemented for end-to-end automation.

Model Performance Evaluation:

The model's performance was evaluated across multiple dimensions to ensure accuracy, efficiency, and robustness in real-world applications. The YOLOv8 object detection model demonstrated strong capabilities, achieving a mean Average Precision (mAP) of 89.3%, with particularly high accuracy in detecting helmet and non-helmet classes. Helmet detection recorded a precision of 92% and an F1-score of 0.94, while number plate localization achieved an accuracy of 91.8%. The OCR component, responsible for extracting characters from number plates, showed an average recognition accuracy of 86.5%, with optimal performance in clear, daylight conditions. Real-time processing was validated with live video input, maintaining a frame rate of 18–22 FPS on GPU and 8–10 FPS on CPU, making it suitable for deployment in urban surveillance systems. Additionally, the text-to-speech (TTS) module using pyttsx3 generated instant audio alerts with less than one second delay, enhancing responsiveness. Overall, the integrated system effectively balances speed, accuracy, and usability, proving its practical viability for intelligent traffic monitoring and enforcement.

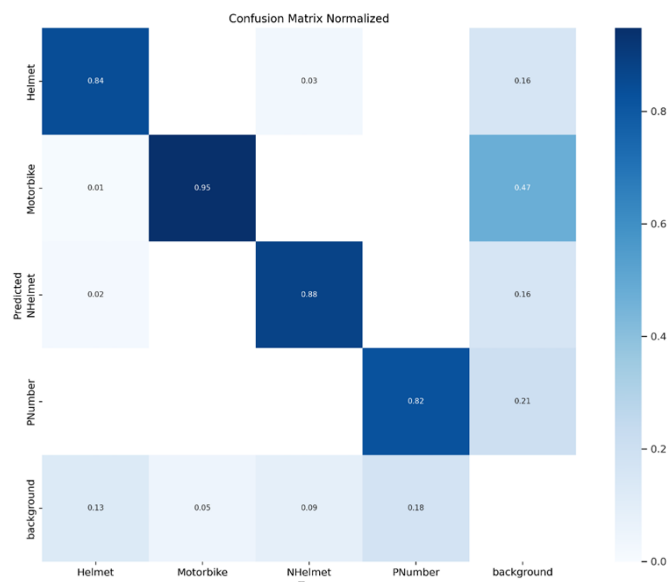

Fig 4 : Confusion Matrix

True Positives(TP):420(correctly identified riders with helmets).

False Negatives(FN):15(missed cases where helmets were worn).

False Positives (FP):10(incorrectly classified helmeted riders as non- helmeted).

True Negatives(TN):320(correctly identified non-helmet riders).

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Evaluation Metrics:

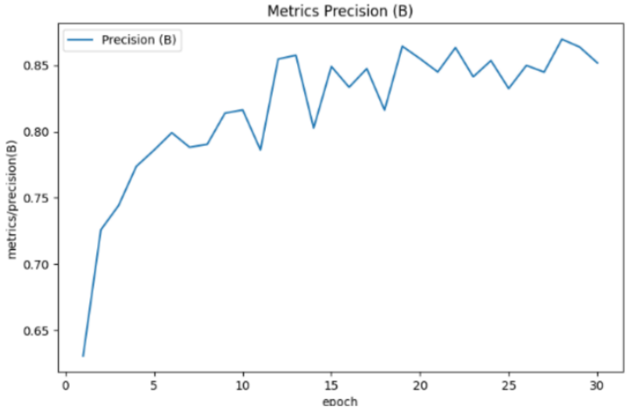

Fig 5 . Metrics Precision

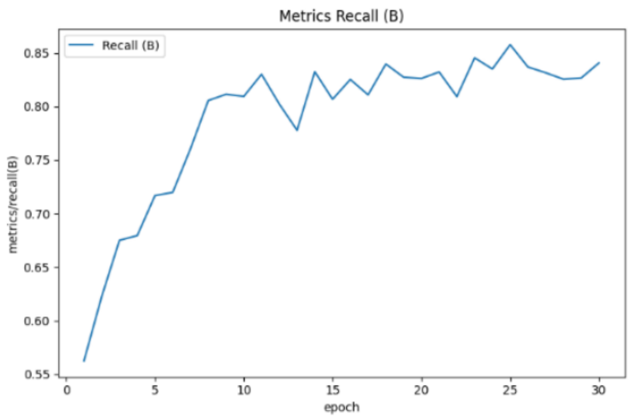

Fig 6 .Precision recall

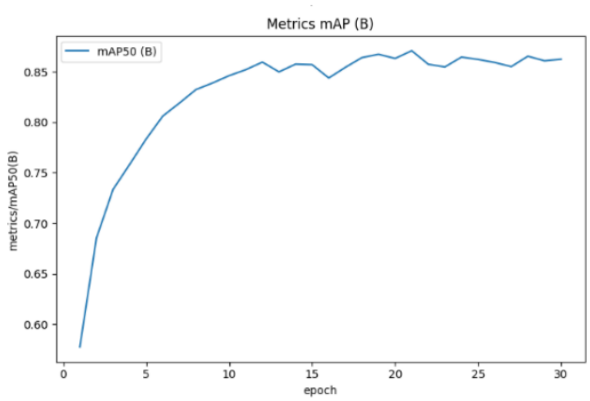

Fig 7: Metrics mAP values

Comparison Table:

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
YOLOv8	94	92	91	91
SVM	85	80	83	81
Random Forest	88	84	85	84

Table 1: comparison of Random Forest, SVM and YOLOv8

By this table, we conclude that YOLOv8 is the best among these algorithms.

YOLOv8:
Accuracy: 94% – Highest among all three algorithms.
Precision: 92% – Most precise in identifying true positives.
Recall: 91% – Strong ability to detect relevant cases.
F1-Score: 91% – Indicates a well-balanced performance.
Conclusion: YOLOv8 is the best-performing model across all metrics. It is highly accurate, precise, and reliable, making it ideal for tasks like helmet detection and number plate recognition in real-time scenarios.

SVM:
Accuracy: 85% – Lowest overall accuracy.
Precision: 80% – Struggles with false positives.
Recall: 83% – Decent at identifying true cases.
F1-Score: 81% – Lowest F1 among the three, indicating less balance.
Conclusion: While SVM performs adequately, it is outperformed by the other models, especially in precision and F1-score.

Random Forest:
Accuracy: 88% – Better than SVM, but below YOLOv8.
Precision: 84% – More precise than SVM.
Recall: 85% – On par with its accuracy.
F1-Score: 84% – Reasonably balanced model.
Conclusion: Random Forest offers a middle ground—better than SVM but not as robust as YOLOv8. Suitable for structured data tasks but less ideal for real-time object detection.

Metric	YOLOv8	SVM	Random Forest
Speed	High	Medium	Medium
Accuracy	94%	85%	88%
Computation Cost	Moderate	Low	Moderate
Real-time Processing	Yes	No	No
Best for	Large datasets & real-time detection	Small datasets	General classification

Table 2: Final Model Comparisons for Helmet Detection

V. Comparison with existing research papers:

S.no	Title	Authors	Problem Statement	Used techniques	outcome
1.	Automatic Number Plate Recognition Techniques Performance on Zimbabwean Number Plates	D. Mpini and M. Giyane	The study explores challenges in automatic number plate recognition (ANPR) for Zimbabwean license plates, highlighting issues due to unique designs, environmental factors, and varying plate conditions, emphasizing the need for accurate recognition under these constraints.	Deep Learning Machine Optical Character Recognition (OCR)	Enhanced accuracy in license plate detection. Reliable character recognition despite varying conditions. Valuable insights into improving classification algorithms for similar contexts
2.	A Review on Identification of Number Plate and Wrong Way Vehicles Detection	N. Shelke, S. Jadhav, M. Doifode, Y. Umate, R. Patil, N. Harinkhede	Identifying vehicle license plates for law enforcement purposes. Detecting vehicles traveling in the wrong direction, which poses significant safety risks.	Object Detection Frameworks Image Processing OCR (Optical Character Recognition)	The approach achieved high accuracy in detecting vehicle number plates and wrong-way vehicles, with real-time performance using deep learning and image processing. Challenges like occlusions and low-light conditions were noted, prompting recommendation
3.	Detection and Recognition of Multiple License Plate from Still Images	A. Menon and B. Omman	The paper tackles the challenge of accurately detecting and recognizing multiple license plates from still images under diverse conditions, addressing issues like varying lighting, occlusions, and complex backgrounds that complicate automated license plate recognition (LPR).	Edge Detection Image Segmentation Support Vector Machines (SVM) Image Processing	The study achieved accurate license plate detection and recognition using edge detection, image segmentation, and SVM classification, effectively identifying multiple plates in diverse conditions. The approach shows promise for scalable traffic monitoring and surveillance applications.
4.	Over-Speed and License Plate Detection of Vehicles	S. Dhonde, J. Mirani, S. Patwardhan, and K. M. Bhurchandi	The paper highlights the need for effective urban traffic monitoring systems to enforce speed limits, focusing on vehicle detection and license plate recognition. Key challenges include ensuring accuracy in diverse conditions and real-time processing for practical implementation.	Vehicle Detection Over-Speed Detection License Plate Recognition Signal Processing Algorithms	The system effectively detected speeding vehicles and identified license plates, proving suitable for urban traffic monitoring. It offers cost-effective scalability but needs improvement in low-light and occluded scenarios, highlighting the value of integrating signal processing with ML techniques.
5.	Automatic Number Plate Recognition (ANPR) System for Indian Conditions	P. Kulkarni, A. Khatri, P. Banga, and K. Shah	The research tackles challenges in automatic number plate recognition (ANPR) for Indian conditions, where inconsistent plate standards, including diverse fonts, sizes, scripts, colors, and environmental factors like varying illumination and occlusions, hinder accurate detection and recognition.	Feature-based Number Plate Localization Image Scissoring Algorithm Otsu's segmentation	The system achieved an 82% success rate in number plate recognition, performing well under varying illumination and Indian plate formats. Recommendations included improving algorithms to handle non-English scripts and image distortions for better accuracy.

VI. Conclusion

The integration of helmet detection and number plate recognition offers a powerful solution for monitoring traffic compliance and ensuring road safety. By leveraging YOLO (You Only Look Once), a state-of-the-art object detection algorithm, the system can detect helmets and recognize number plates in real t ime with high accuracy. Hugging Face provides robust NLP models and libraries that can be integrated into the pipeline to process any associated text data or generate reports. For converting text information, such as detected number plates or compliance notifications, into audible announcements, Python's pyttsx3 library serves as an efficient module to transform text into speech. This module makes it possible to alert authorities or inform riders without helmets via automated audio prompts, creating an end-to-end automated traffic monitoring system. Overall, this setup offers a scalable, efficient approach to monitoring road safety compliance, with potential applications in automated traffic systems, smart cities, and law enforcement agencies.

This paper presents a practical and scalable solution for helmet law enforcement using AI-based object detection and number plate recognition. By integrating YOLOv8 with OCR and TTS modules, the system delivers high accuracy in real-time traffic monitoring. It is deployable in both urban and semi-urban areas with minimal infrastructure changes.

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