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AI-Driven Safety: Automated Helmet Detection and License Plate Recognition

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***Abstract*—This research study addresses the increasing need for automated traffic enforcement solutions to improve road safety, focusing on helmet detection and license plate recognition for motorcyclists. With manual enforcement limited by factors such as human error, fatigue, and the sheer volume of traffic, an AI-driven system offers a scalable alternative. Leveraging YOLOv8 for object detection and EasyOCR for text extraction, the proposed system automates the detection of helmet violations and vehicle identification through number plates. The model operates by first detecting helmet usage, and if absent, proceeds to recognize the vehicle's number plate. It performs reliably in various challenging conditions like poor lighting, occlusion, and motion blur, making it suitable for real-time traffic monitoring. The research also addresses ethical considerations around privacy and data protection, ensuring compliance with legal standards. By reducing manual intervention, this solution enhances traffic enforcement efficiency, promotes road safety, and provides a scalable approach to monitoring traffic violations.**

Keywords—Helmet detection, License plate recognition, YOLOv8, Optical Character Recognition (OCR), Automated traffic enforcement, Real-time object detection

I. INTRODUCTION

Traffic enforcement has several difficulties because of the motorized transportation sector's explosive expansion, especially in densely populated metropolitan areas. Conventional traffic law enforcement and monitoring techniques, such using number plates to identify vehicles or verifying helmet use, mostly rely on manual procedures. These methods require a lot of labor and are prone to inefficiencies and human mistakes. The sheer volume of traffic, tiredness, and poor visibility are some of the factors that make it challenging for law enforcement to continuously monitor breaches. This is where automated systems come into play, providing a more dependable and expandable traffic monitoring solution.

Motorcycle riders' use of helmets, which is crucial for rider safety, is one important concern. But a lot of motorcyclists disregard this safety precaution, which raises the possibility of serious injuries in collisions. Furthermore, manual helmet violation detection is ineffective and frequently misses most violators. In addition, it becomes crucial to identify the offenders based on their license plates; yet, the accuracy of the present manual approaches is poor, particularly under difficult circumstances like dim illumination or fast-moving traffic [1]. Due to these constraints, a sophisticated, automated system that can identify vehicles and detect helmet use is required.

This study suggests an AI-powered method to automatically identify license plate recognition and helmet infractions in response to these difficulties. The system attempts to offer a real-time, accurate, and scalable substitute for conventional approaches by utilizing deep learning models such as YOLOv8 for object identification and EasyOCR for text extraction. YOLOv8 uses real-time bounding box and class label prediction to identify objects in photos. Annotated datasets comprising pictures of bikers wearing and not wearing helmets are used to train the model.

Because of its cutting-edge performance in object detection tasks, YOLOv8 was selected. It is perfect for real-time applications like traffic monitoring because it strikes a balance between speed and accuracy. The enhanced design and efficiency of YOLOv8 over earlier iterations enable it to recognize helmets, riders, and license plates with excellent accuracy in difficult-to-reach situations.

Using number plate recognition, the system systematically detects helmets and recognizes automobiles while overcoming typical obstacles including motion blur, occlusion, and illumination fluctuations. Through the provision of an automated and effective tool for law enforcement authorities to monitor and enforce traffic laws, this research seeks to improve road safety.

II. LITERATURE SURVEY

The use of computer vision and deep learning techniques for real-time detection and identification in traffic enforcement has been extensively researched. One crucial area of focus is the detection of helmets and identification of vehicle number plates, which play a key role in ensuring compliance with road safety regulations. Among the prominent models used for this task is the YOLO (You Only Look Once) model, known for its real-time object recognition capabilities. Due to its efficiency, YOLO has been widely adopted in helmet detection and number plate recognition systems [2].

A study on real-time helmet and license plate detection using YOLOv5 demonstrated significant improvements in both detection accuracy and efficiency. However, this study also highlighted the challenges posed by high-quality image requirements and complex conditions, such as varied lighting and fast-moving vehicles, which can affect the system's performance [3]. Despite these challenges, the application of deep learning models like YOLOv5 is a step forward in automating traffic enforcement tasks, offering promising results in real-world scenarios.

Further advancements in license plate recognition were explored in another study, which focused on improving image quality through noise reduction and edge detection algorithms. These techniques helped in enhancing the clarity of license plate images, especially under difficult conditions, but low-resolution images remained a significant hurdle. The study pointed out that factors such as camera quality, plate angle, and motion blur could negatively impact the accuracy of recognition [4].

Another research effort introduced a more sophisticated approach using Swin Transformers for helmet detection [5]. This study tackled complex challenges like class imbalance and model robustness by applying advanced techniques such as custom loss functions. However, the approach required substantial computational resources, which could limit its applicability in real-time systems. The study also raised concerns about potential overfitting, especially when working with smaller datasets [6]. This indicates the need for more balanced and optimized models that can perform efficiently in a variety of environments without sacrificing accuracy.

In addition, lightweight algorithms for helmet violation detection have been explored in some research. These algorithms, which rely on factors such as color contrast and contour analysis, offer quicker results and are suitable for real-time deployment [7]. However, they also face limitations in complex environments, such as those with similar-colored headgear, leading to false positives. Improving robustness in such scenarios is an ongoing challenge, and more work is needed to refine these detection systems for better accuracy across diverse settings [8].

Collectively, these studies highlight the significant progress made in helmet and license plate detection using deep learning models, but they also point to the unresolved issues that still require attention. Real-time processing capabilities, for instance, are a major area that needs optimization, as high computational requirements can slow down performance in practical applications. Moreover, challenging conditions such as occlusions, low lighting, and motion blur continue to pose difficulties for accurate detection.

To sum up, while the integration of deep learning models like YOLO with OCR systems has advanced traffic enforcement, there are still obstacles that need to be addressed. These include improving the system's accuracy in challenging environments, ensuring the performance remains efficient for real-time processing, and addressing ethical concerns related to data privacy. creation of an automated system that uses EasyOCR and YOLOv8 for license plate recognition and helmet detection.

application of preprocessing methods to improve OCR accuracy and detection.

Real-time traffic monitoring capabilities under a variety of circumstances, such as dim lighting and motion blur, are demonstrated.

Performance comparison of the suggested system with current techniques, demonstrating its increased scalability and accuracy. Future research should focus on refining detection algorithms, expanding the training datasets, and establishing clear legal frameworks to support the widespread implementation of these systems. By addressing these areas, traffic enforcement can benefit from more robust, scalable, and reliable automated systems [9].

III. METHODOLOGY

This section describes how deep learning techniques—YOLOv8 for object detection and EasyOCR for text extraction—were used to construct the automatic helmet identification and number plate recognition system. Preprocessing of the dataset, model selection, training, data augmentation, and performance assessment are some of the crucial steps in the process.

1. Model Selection and Instruction

A state-of-the-art method for object detection called YOLO (You Only Look Once) treats the job as a single regression issue, enabling real-time recognition. It produces fast and precise identification by dividing the input image into a grid and simultaneously predicting bounding boxes and class probabilities. The YOLOv8 version is more efficient and better designed than its predecessors. It is available in four different sizes, each of which is tailored to a certain application: n (nano), s (small), m (medium), and l (large). By approaching the job as a single regression issue, the state-of-the-art object detection method YOLO (You Only Look Once) enables real-time recognition. To achieve fast and precise identification, it splits the input picture into a grid and simultaneously forecasts bounding boxes and class probabilities. With four alternative sizes (nano), s (small), m (medium), and l (large)each tailored to a different application, the YOLOv8 version outperforms its predecessors in terms of architecture and efficiency. The micro version is lightweight for speed on low-power devices, whilst the small, medium, and large versions strike a balance between speed and accuracy, with larger models often giving higher precision at the expense of increased computing needs. YOLOv8's adaptability makes it excellent for a variety of purposes, including real-time video analysis and embedded devices.

The study's dataset includes the data collected from both local traffic scenarios and images collected from public traffic datasets (such as "Cityscapes" and "Aerial Imagery"). Ten thousand annotated photos are included, five thousand of which are for license plate recognition and five thousand for helmet/no helmet detection. There are several license plate styles, riders wearing helmets, and riders not wearing them.

Model 1: This model was taught to identify several items in traffic scenarios, including riders, helmets, and license plates. This model's objective is to locate these items using bounding boxes in the input picture and determine if they are there. A dataset of annotated photos was used to train Model 1, which is based on YOLOv8, through supervised learning. Bounding boxes for riders, helmets, and license plates were used to identify each image. To enhance generalization, the training process used methods including data augmentation (rotation, flipping, and scaling). The Adam optimizer with a learning rate of 0.001 was used to optimize the model.

Model 2: An advanced model designed specifically for accurate number plate recognition. To increase OCR accuracy, a second model is being used to fine-tune the number plate localization.

Using unique datasets containing annotated photos of cyclists, helmets, and license plates, both models were trained. Number plate photos with extremely precise bounding box annotations were used to train Model 2, which is more sensitive to number plates.

2. Preprocessing Images

Greyscale Conversion: To save computing complexity, the input image was converted to greyscale as colour information is not necessary for identifying helmets, riders, and number plates. Preprocessing the input photos with techniques like denoising, brightness/contrast improvement, and greyscale conversion can improve recognition. Accurate recognition is also enhanced by employing larger, more varied datasets, sophisticated model training methods, and data augmentation.

Contrast and Brightness Enhancement: To improve the greyscale image's brightness and contrast, a linear modification was used. The following formula describes the transformation:

$$I_{new} = \alpha \cdot I_{gray} + B_i \qquad [1]$$

where β is a brightness factor (set to 50), α is a contrast factor (set to 2), and Inew is the improved image. This enhances the objects' visibility under different lighting circumstances, especially the writing on the license plate.

Binarization (Thresholding): The preprocessed picture is binarized to help the text on the license plate stand out for the OCR engine. This increases the text's visibility, which makes the OCR work easier.

Denoising: To lessen noise in the picture that might obstruct text recognition and object detection, a median blur filter is performed. Denoising smoothens out little flaws while preserving significant edges and structures. [10]

The You Only Look Once (YOLO) [11] family of object detection models' most recent version, YOLOv8, was selected due to its exceptional speed and accuracy in real-time detection tasks. With enhanced architectural optimization, YOLOv8 surpasses its predecessors in its ability to recognize helmets and other items more accurately under a variety of situations [12].

The following is how the helmet detection phase works:

● The YOLOv8 model receives input photos and evaluates them in real-time to determine if a helmet is present.

● Bounding boxes with confidence score for helmet detection are created around items that are identified.

● If a helmet be identified, the image is marked as "Helmet Detected" by the system, and no more steps are taken. The algorithm moves on to number plate detection if there is not a helmet identified.

3. Object Identification and Boundary Box Modification

The improved image is sent into Model 1 after preprocessing, and it can identify several things, including helmets, riders, and license plates. YOLOv8 generates bounding boxes with object classes after processing the input picture in a single forward pass [13]. The characteristics of every detection are as follows:

· Bounding Box Coordinates (x1, y1, x2, y2): The corners of the items that were identified are on the top-left (x1, y1) and bottom-right (x2, y2) respectively.

· Class ID: The anticipated class label (such as rider, helmet, or number plate).

The Confidence Score indicates the likelihood that the item being identified is a member of the anticipated class. [14]

Bounding boxes and class labels are created in the picture for each object that is recognized. The number plate is the primary class of interest. YOLOv8's bounding box outputs were used to classify helmets and non-helmets. The system determines if a helmet is worn by each rider it detects. The rider is considered to be wearing a helmet if a bounding box marked "helmet" confidently overflows the area of the rider's head. It is marked as a violation otherwise.

4. Expanded Bounding Box

To guarantee that the complete number plate is recorded for precise OCR, the associated bounding box is significantly extended once a number plate is recognized [15]. Using the formulas listed below, a scaling factor is applied to the original coordinates to increase the bounding box.

$$x1_{new} = max(0, x1 - scale\_factor \cdot width) \qquad [2]$$

$$y1_{new} = max(0, y1 - scale\_factor \cdot height) \quad [3]$$

$$x2_{new} = min(image\_width, x2 + scale\_factor \cdot width) \quad [4]$$

$$y2_{new} = min(image\_width, y2 + scale\_factor \cdot height) \quad [5]$$

Where scale_factor scale_factor is the scaling factor used to enlarge the bounding box, width and height are the dimensions of the bounding box, image_width image_width is the width of the entire image, and x 1 x 1 , y 1 y 1 , x 2 x 2 , y 2 y 2 represent the original coordinates of the bounding box

5. EasyOCR for Optical Character Recognition (OCR)

Following exact localization of the number plate, the cropped number plate picture is subjected to OCR processing via the EasyOCR library. To improve the resolution and make the text easier for the OCR engine to read, the cropped number plate image is enlarged [16]. There is a two-fold scaling applied to the width and height. The system uses EasyOCR to process the license plate when it detects a helmet violation. After cropping the image and applying contrast correction and binarization, the number plate area is supplied into the OCR module. After that, the captured text is stored for future use.

The cropped plate picture and the final processed image (complete with labels and bounding boxes) are saved by the system for further examination. For usage in applications such as car identification or traffic monitoring, the extracted text can be shown or saved. By combining optical character recognition (EasyOCR) and object detection (YOLOv8), the system becomes automated. Without requiring human assistance, it automates the process of detecting the helmet, detecting infractions, and obtaining vehicle information from the license plate.

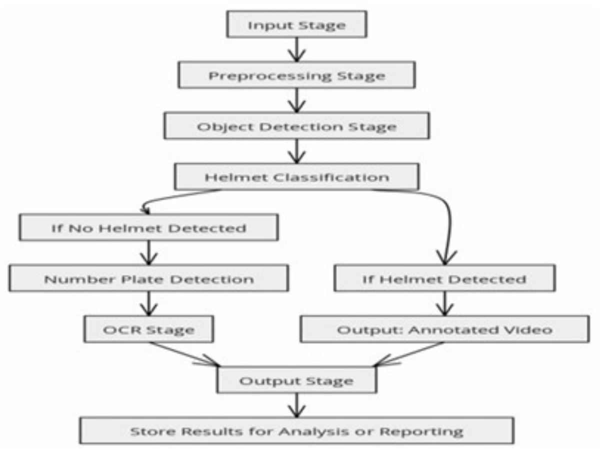

Figure 1: Flowchart illustrates the methodology for helmet detection and number plate recognition, including object detection, helmet classification, and OCR for non-helmet cases.

IV. METRICS USED

For the item detection task (helmets, riders, and number plates), accuracy, recall, F1-score, and mean Average accuracy (mAP) are the main assessment measures [17]. During training and testing, these metrics were computed on the validation dataset.

Precision: The number of relevant (properly identified) items discovered is measured by precision. Fewer false positives are indicated by high precision. When identifying helmets or number plates, for example, it counts the proportion of detected bounding boxes that match real helmets or plates.

$$Precision = \frac{TP}{TP+FP} \quad [6]$$

where TP stands for True Positives and FP stands for False Positives.

Recall: Recall evaluates the system's capacity to identify every pertinent object. When a model has a high recall value, false negatives are reduced since it can identify most helmets, riders, or number plates in the picture.

$$Recall = \frac{TP}{TP+FN} \quad [7]$$

where TP stands for True Positives and FN stands for False Negatives.

F1-score: The harmonic mean of recall and accuracy is the F1-score. When recall and accuracy are equally significant, as they often are when there is an imbalance between false positives and false negatives, it offers a fair assessment metric.

$$F1 - score = 2 \cdot \frac{P \cdot R}{P+R} \quad [8]$$

where P stands for Precision and R stands for Recall.

Mean Average Precision (mAP): This metric is commonly used to evaluate object detection algorithms. It calculates the area under the precision-recall curve, considering every object detected at different confidence thresholds. For YOLOv8, mAP is typically computed at intersection-over-union (IoU) thresholds of 0.5 (mAP@0.5) and across a range of IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95).

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \quad [9]$$

where AP stands for Average Precision and 'n' stands for the total number of classes.

V. RESULTS

The suggested method, which combines YOLOv8 for object identification with EasyOCR for text recognition, performs well in identifying helmets, riders, and number plates in traffic situations. Initially, the YOLOv8n model was employed, but due to relatively lower performance on the helmet dataset, the model was shifted to YOLOv8s for improved accuracy across both the helmet and number plate datasets. The YOLOv8s model significantly enhances detection precision and recall, resulting in better overall performance. The model minimizes false detections by accurately identifying helmets and riders, and using a two-stage technique improves accuracy for number plate identification, ensuring precise localization for further OCR processing. Even under difficult conditions like varying illumination and picture noise, the OCR system functions effectively, accurately recognizing text on license plates. The system is suitable for real-time traffic enforcement and monitoring due to its overall effectiveness and efficiency. A table comparing the performance of both models is provided below.

Metric	YOLOv8n Model	YOLOv8s Model
Box Precision (P)	0.76	0.937
Recall (R)	0.818	0.926
mAP50	0.832	0.958
mAP50-95	0.511	0.818

Table 1. Comparison of the 2 model variations

With a recall of 92.6% and an overall accuracy of 93.7%, the detecting system performs admirably. With a high mAP50 of 95.8% and mAP50-95 of 81.8%, it is excellent at identifying riders and number plates. Due to its high degree of accuracy in recognising riders, helmets, and license plates, the model is a good fit for duties involving traffic enforcement and surveillance.

	Class	Box Precision (P)	Recall (R)	mAP50	mAP50-95
0	all	0.937	0.926	0.958	0.818
1	with_helmet	0.915	0.923	0.933	0.767
2	without_helmet	0.894	0.867	0.954	0.753
3	rider	0.987	0.913	0.954	0.926
5	number_plate	0.957	0.986	0.972	0.842

Table 2. Cumulative findings of the models

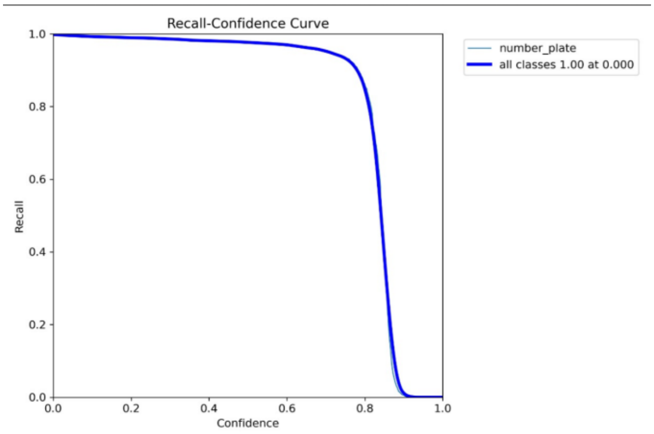

Fig 2: Recall-Confidence curve of the number plate detection model

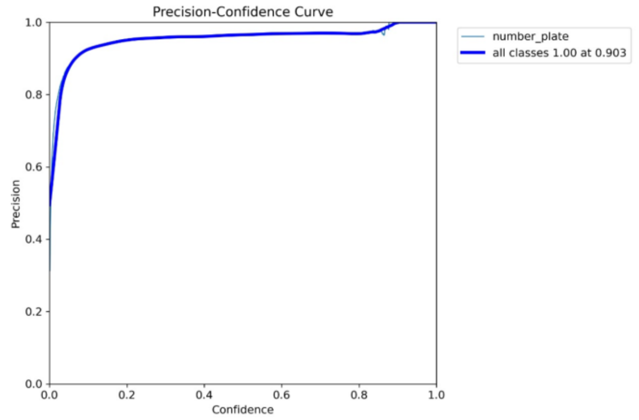

Fig 3: Precision-Confidence curve of the number plate detection model

Figures 2 and 3 show the performance of the number plate detection model using Recall-Confidence and Precision-Confidence curves. Figure 2 indicates that the model has a high recall across various confidence thresholds, efficiently detecting most number plates, albeit recall decreases at higher confidence levels as the model eliminates false positives. Figure 3 displays the Precision-Confidence curve, which approaches 1.0, suggesting that as confidence increases, the accuracy of detected number plates improves dramatically with few false positives. The suggested system, which combined YOLOv8 and EasyOCR, outperformed previous techniques like YOLOv5 and Swin Transformers, with a detection accuracy of 93.7% with a mAP@0.5 of 95.8%. While retaining real-time processing capabilities, the system outperformed current approaches in difficult scenarios (such as dim lighting and motion blur).

These curves demonstrate that the number plate identification model maintains a strong balance of precision and recall, making it ideal for real-time traffic enforcement applications.

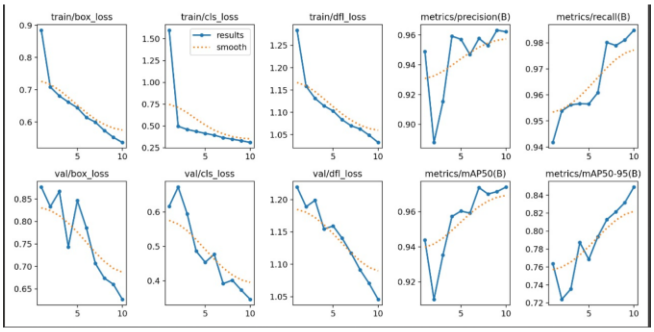

Fig 4: Graphs of Loss and Metrics measured during the Training.

An overview of the training and validation metrics during the model's training phase is shown in Figure 4. As training proceeds, the model's capacity to precisely forecast bounding boxes and categorize objects is demonstrated by a steady decline in the training box loss, classification loss, and distribution focal loss (DFL). **Precision** and **recall** increase significantly, highlighting the model's ability to minimize false positives and correctly detect relevant objects, reducing false negatives. On the validation side, despite some initial fluctuations, the **validation box loss**, **classification loss**, and **DFL loss** show a general downward trend, reflecting better generalization and localization on unseen data. Lastly, the

mAP@0.50 improves, confirming that the model is becoming more effective at predicting object locations with acceptable accuracy. Overall, these metrics collectively show that the model is learning and performing well on both training and validation datasets. The below figures depict the output of detection of helmet and number plate:

Fig 5: Sample Output from the Result

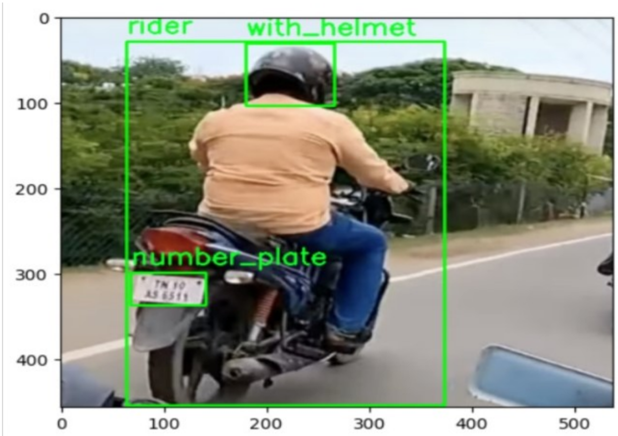

Fig 6: Sample Output from the Result

VI. CONCLUSION

To sum up, this study effectively used YOLOv8 for object identification and EasyOCR for text extraction to apply a deep learning-based method for automatic helmet detection and number plate recognition. The model demonstrated improved accuracy in identifying helmets and extracting number plate information through careful preprocessing, model training, data augmentation, and performance evaluation. Metrics such as precision, recall, and mean Average Precision depict that the system can minimize false positives and false negatives while generalizing well to unseen data. Despite the progress, there are several areas for future research. One promising direction involves enhancing the model's robustness in challenging conditions, such as detecting helmets and number plates in poor lighting or under occlusions. Additionally, future work could explore multi-class helmet classification, such as distinguishing between various helmet types, and improving number plate recognition by integrating more advanced OCR techniques. Another important aspect for future development is the incorporation of real-time processing capabilities and deployment on edge devices to facilitate real-time surveillance in traffic monitoring systems. By addressing these areas, this research contributes to various highly effective and scalable solutions for road safety and law enforcement applications.

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