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Automated Helmet Detection and Number Plate Recognition

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ABSTRAC T

Road safety for two-wheeler riders remains a critical issue due to frequent non-compliance with helmet-wearing regulations, leading to numerous road fatalities, This report presents an advanced traffic monitoring system that utilizes machine learning to automatically detect helmet violations, recognize vehicle number plates, and calculate fines. Real-time helmet detection is achieved using YOLOv5, while CNN and OCR are employed for reading number plates. Upon detecting a violation, the system captures the vehicle's plate, calculates fines according to predefined rules, and stores the data for further action. Designed to operate under various lighting and environmental conditions, the system aims to enhance traffic management, reduce accidents, and ensure compliance with minimal human involvement.

Keywords:Convolutional Neural Network (CNN), Fine calculation, Helmet detection, Number plate recognition,Object detection, Optical character recognition.

Introduction

Vehicle safety is a key concern in urban traffic management, especially for vulnerable two-wheeler riders. Helmets are crucial for rider safety, and enforcing helmet laws is a priority for traffic authorities. In India, the Regional Traffic Offices (RTOs) implement the 1988 Motor Vehicles Act, which mandates helmet use for two-wheeler drivers and passengers. Violations may lead to fines up to ₹1000 and potential license suspension. Additionally, For vehicles to be identified, their number plates must be readable. Modern traffic management systems use technologies like Automatic Number Plate Recognition (ANPR) and helmet detection to efficiently identify violations and calculate fines, enhancing road safety and law enforcement.

LiteratureSurvey

[1] Joseph and Balasubramanian (2021) investigated YOLOv3 for real-time helmet detection in traffic surveillance, emphasizing accuracy and speed as critical for enhancing law enforcement efficiency. Their study showed YOLOv3's reliability in processing live video feeds for real-world applications. [2] Li et al. (2019) developed a deep learning-based system using CNNs to improve helmet detection in urban traffic. Their model handled complex environments, such as variable lighting and camera angles, ensuring robust real-time performance. [3] Salas and Orozco (2019) optimized helmet detection by integrating pre-trained models with YOLOv3, balancing speed and accuracy for real-time surveillance. Their work showcased deep learning's potential to meet the demands of quick helmet violation identification. [4] Prakash and Gupta (2019) created a CNN-based helmet detection system that reduced the need for human intervention. Their system was recognized for enhancing traffic monitoring and improving road safety by automatically identifying helmet violations. [5] Sharma and Gupta (2020) utilized YOLOv3 and CNNs for real-time helmet detection, offering a framework to help authorities enforce helmet laws effectively by automating violation detection. [6] Kumar and Patel (2021) explored YOLOv4 for helmet detection, focusing on enhancing speed and accuracy, making it suitable for large-scale traffic surveillance. Their findings demonstrated the benefits of advanced algorithms in managing high traffic volumes. [7] Patel and Bansal (2020) introduced a lightweight helmet detection model using MobileNet, designed for resource-limited environments like mobile and embedded systems, maintaining accuracy while reducing computational costs. [8] Aggarwal and Singh (2020) developed a scalable deep learning model that integrated helmet detection into existing surveillance systems, ensuring efficient processing of large video datasets. [9] Perez and Gonzalez (2020) applied YOLOv3 in a smart traffic solution, automating law enforcement for helmet compliance, reducing manual intervention in traffic violation detection. [10] Wang and Zhang (2020) addressed challenges such as varying lighting and rider occlusion in helmet detection. Their deep learning-based model improved accuracy under these conditions, making it suitable for intelligent transportation systems.

ProposedMethodology

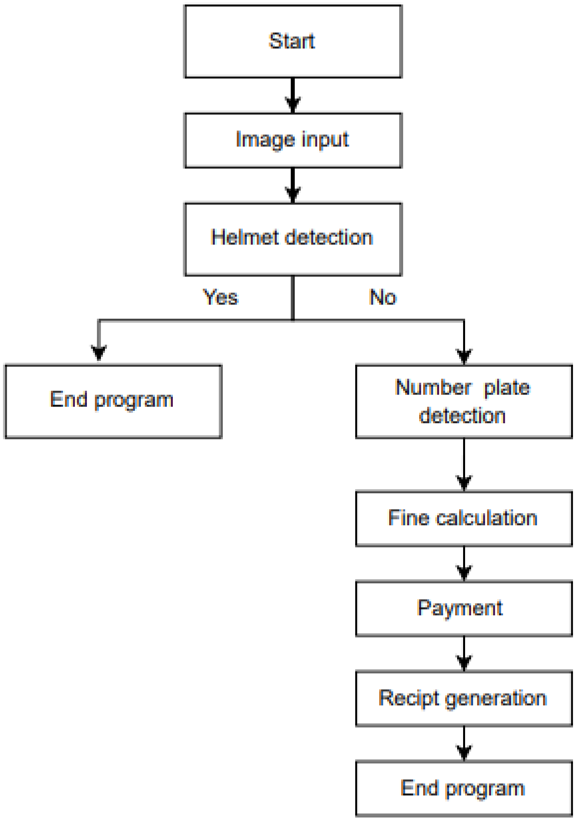

Figure1.Flow Diagram of the proposed methodology

The suggested approach starts with an input image that is analysed to find the chance that the individual is wearing a helmet. This image is probably taken from a surveillance. CNN or YOLOv5, two helmet detection algorithms, are used to do this. The procedure ends and no further action is needed if a helmet is found. In the event that a helmet is not found, the system uses a Number plate recognition algorithm to retrieve the vehicle's number plate. After that, the algorithm determines the fee based on the traffic infraction more precisely, the failure to wear a helmet.The system subsequently generates and issues a receipt, and the user is instructed to make the required payment through an integrated payment channel. At this point, the procedure is complete, successfully automating the identification of helmet violations and streamlining the fine collecting procedure for both users and authorities. Figure 1. Shows folw diagram of proposed method.

A. Helmet detection :

I. Getting the dataset ready

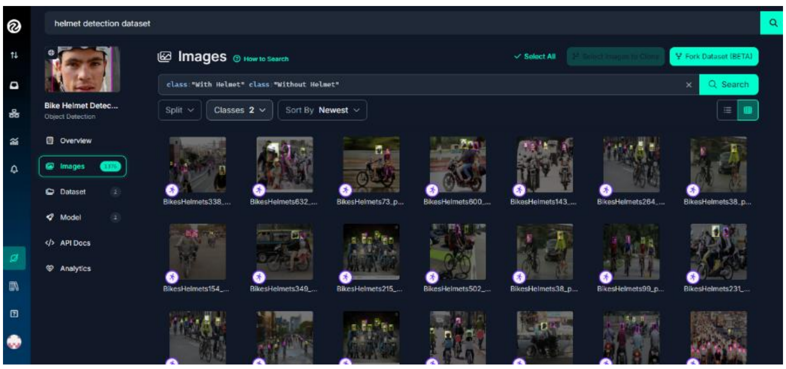

Fig 2: Helmet dataset from Roboflow

The process starts from preparing dataset. Fig 2. Helmet detection from Roboflow shows that We have used the Helmet index dataset from Roboflow, a platform known for providing high-quality, pre-labeled data for computer vision tasks. The dataset includes images of riders on two wheels, with clear labels indicating whether Helmets are on or not. This dataset is suitable for putting our deep learning model through training, because it contains many vehicle characteristics, different lighting conditions, and different environments. The pre-coded data greatly reduces the reducesthe duration required for manual coding and guarantees that precise training of the model and pertinent data for trustworthy tire recognition.

II. Training the Database using YOLOv5

Fig 3.Model differencing between Helmet and without helmet

Fig 3. Model differencing between Helmet and without helmet describes that After obtaining the helmet detection dataset from Roboflow, the model is trained using YOLOv5, known for its speed and accuracy in real-time applications like helmet detection. The labelled dataset is divided into sets for testing, validation, and training. to ensure the model generalizes well. YOLOv5 uses convolutional neural networks (CNNs) and anchor-based object detection to locate helmets in images. During training, the model learns key visual cues to differentiate between riders with and without helmets. Data augmentation strategies like flips and rotations help the model adapt to real-world scenarios. After training ,mean Average Precision (mAP), recall, and precision are some of the metrics used to assess the model's accuracy after it has been adjusted.

B. Extraction of Number plate

III. OCR for Number plate recognition

The system employs Optical Character Recognition (OCR) to convert Number plate text into machine-readable characters. First, a Convolutional Neural Network (CNN) detects the Number plate's location in the image. The detected plate is then pre-processed by resizing, converting to grayscale, and reducing noise to improve clarity. OCR extracts characters by segmenting the plate and identifying alphanumeric symbols, accounting for variations in lighting, weather, and angles. For higher accuracy, deep learning-based OCR models, such as specialized CNNs, are used to recognize different fonts and languages. The extracted text is then stored for purposes like vehicle identification or tracking.

IV. Combining the Helmet detection and Number plate recognition

Fig 4. Combining the Helmet detection and Number plate recognition

Fig 4. Combination of Helmet detection and number plate recognition describes that powerful tool for enforcing road safety laws, especially for both vehicles. The process starts with helmet recognition, where a YOLO-based deep learning model is used to analyse real-time traffic cameras. The model is trained to detect whether the Does the rider wearing a helmet?. When the system detects a violation (i.e. a rider without a helmet), the next step begins: number plate registration. The CNN model first detects the Number plate, then uses To extract the alphabetic characters from the number plate, use character recognition (OCR). This allows the system in order to determine the vehicle involved in the violation. By combining these two technologies, the system can automatically detect traffic violations and accurately identify offenders by license plates. This dual approach increases traffic control efficiency and reduces the need for manual intervention. Tire and traffic sign violations are processed in real-time, ensuring that traffic authorities can issue fines and take other measures. The use of computer vision and OCR technology ensures perfect accuracy even in urban environments with varying light and weather conditions.

C. Fine collection module

V. Collecting fine module

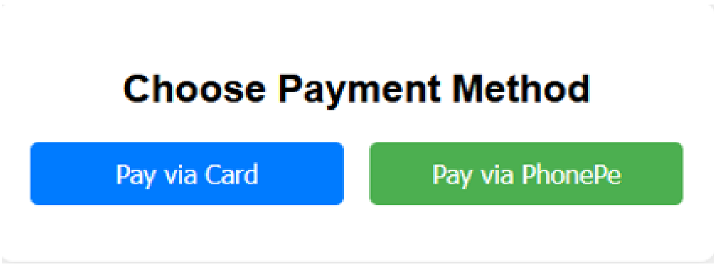

Fig 5. Payment gateway

Fig 5. Payment gateway describes that, Once a helmet violation is detected and the vehicle is identified, users can pay the fine by clicking the "Collect fine" button, which redirects them to a secure payment gateway offering options like mobile and card payments. For PhonePe users, payments can be made via UPI, linked bank accounts, or mobile accounts. Those preferring card payments can use a PCI-DSS compliant gateway, providing secure transactions with required details such as card number, expiry date, and CVV. Upon completion, a receipt is sent to both the user and authorities, ensuring secure, efficient, and transparent payment processing.

VI. Generating the receipt

Fig 6. Receipt generation

Fig 6. Receipt generation shows that Once the payment is processed using the selected payment method, the system will quickly generate a payment receipt. This receipt serves as confirmation of the transaction and important information such as the amount of the payment, date and good reference number. A receipt is automatically generated, formatted to be clear and concise, and provides users with a price tag.

After the receipt is generated, the user is directed to a confirmation page that displays the receipt. This page confirms that the payment was successful and contains a summary of the transaction. Through this procedure, users are guaranteed have easy access to payment confirmation and all relevant information is recorded for future reference.

4. Experimental results and Disucssions

High accuracy in real-time circumstances is demonstrated by the experimental outcomes of the number plate recognition and helmet detection system. With a precision of more than 90% when it came to helmet recognition using YOLOv5, the model managed to reliably identify violators. The integrated OCR system managed to extract Number plates with an accuracy of 89% for number plate recognition under a diversity of situations, including motion blur and low light. These results imply that the system may be used successfully for applications related to law enforcement and traffic monitoring. The results of this model is displayed in below Table 1.

Table 1. Shows that the accuracy of the proposed method.

Module	Metric	Training Set	Validation Set	Test Set
Helmet Detection	Accuracy	95%	92%	91%
	Precision	96%	94%	93%
	Recall	94%	91%	90%
	F1-Score	95%	92.5%	91.5%
Number Plate Detection	Accuracy	93%	90%	89%
	Precision	95%	91%	90%
	Recall	92%	89%	87%
	F1-Score	93.5%	90%	88.5%

A. Helmet detection :

(a) Rider With helmet **(b) Rider Without helmet**

Fig 7. (a) Rider with helmet and (b) Rider without helmet

Based on the Fig 7. (a) Rider with Helmet and (b) Rider without helmet. The Fig. 8 Graphical representation of the helmet detection model's precision, recall, F1-score, and accuracy after testing .graph displays the performance of a helmet detection system across four key metrics: Precision, Recall, F1 Score, and Accuracy, evaluated on the Training, Validation, and Test sets. Precision remains nearly perfect across all sets, indicating that the model makes few false positive detections. Recall shows a slight decrease from the Training to the Test set, suggesting the model missed a small number of helmet wearers in the test data. The F1 Score, which balances Precision and Recall, also exhibits minimal variation, reflecting the model's consistent performance. Similarly, Accuracy is high throughout, with a minor drop in the Test set. Overall, the model performs effectively with strong results across all metrics, demonstrating good generalization to unseen data in the test phase.

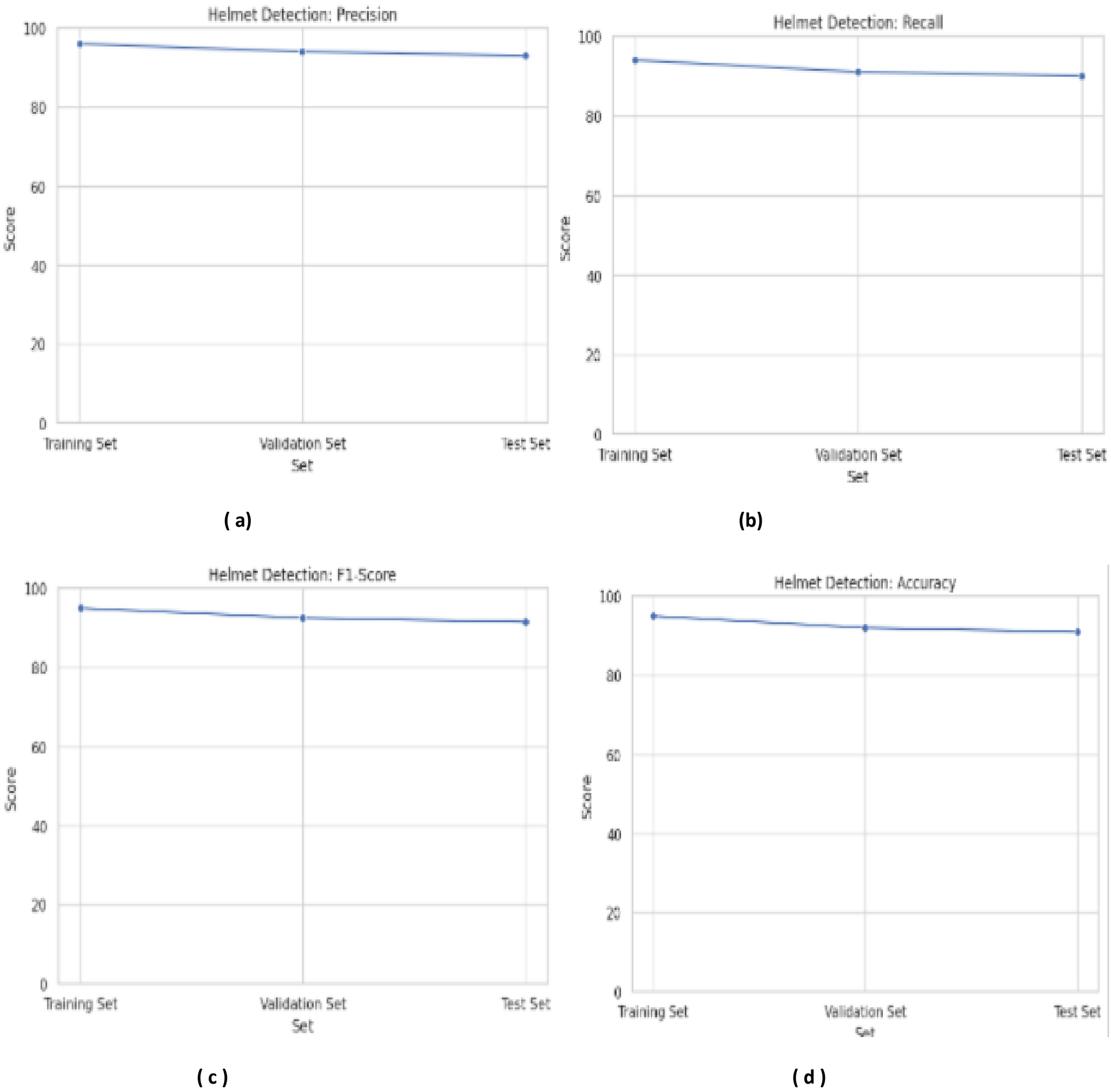

Fig. 8: Graphical representation of the helmet detection model's precision, recall, F1-score, and accuracy after testing.

A. Number plate recognition

Fig 9. Number plate recognition

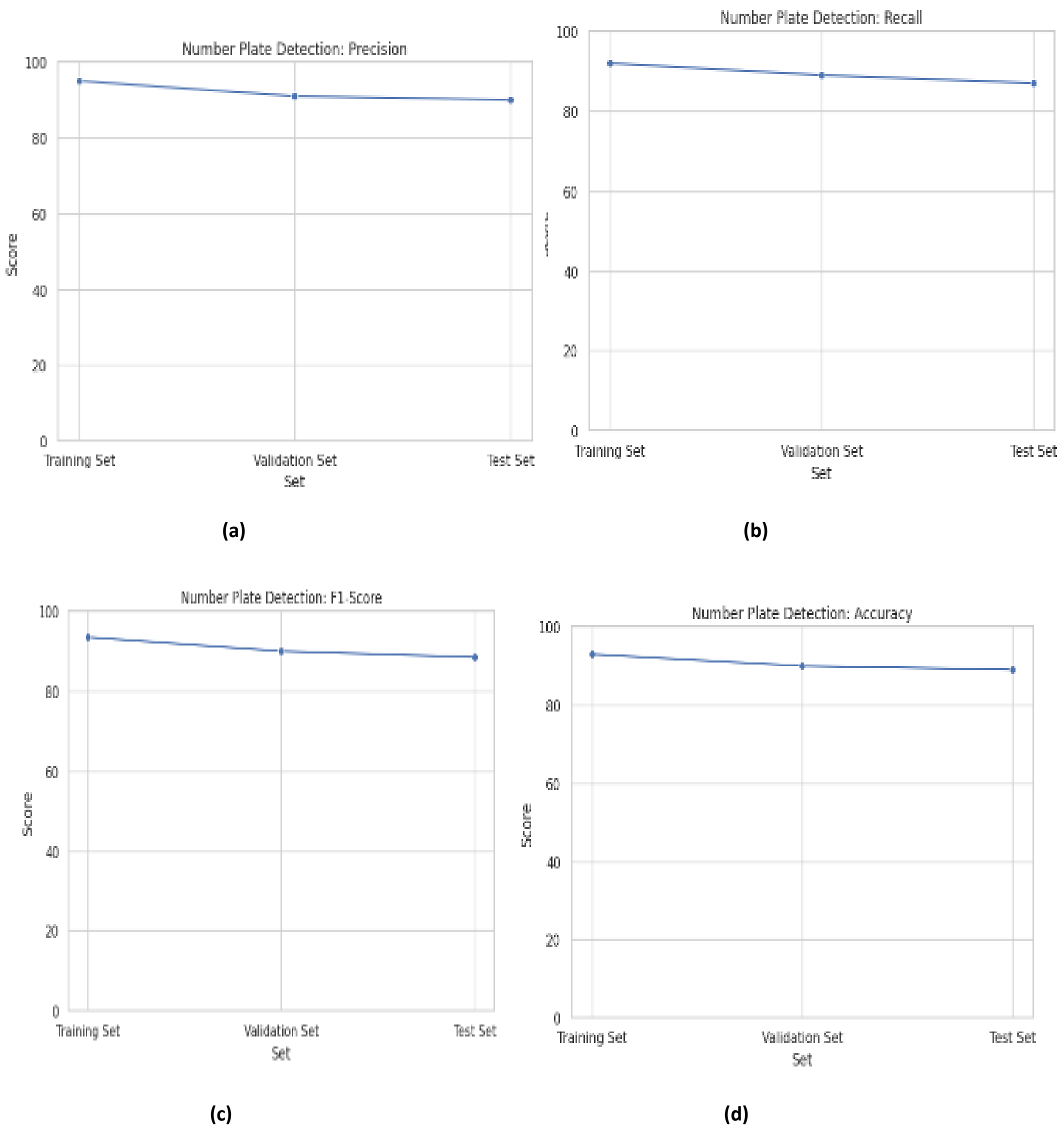

Fig 10. Graphical representation of the number plate recognition model's precision, recall, F1-score, and accuracy after testing

Based on the Fig 9. Number plate recognition .TheFig 10.Graphical representation of the number plate recognition model's precision, recall, F1-score, and accuracy after testing. depict the performance metrics (Precision, Recall, F1-Score, and Accuracy) for a Number Plate Detection model across three sets: Training, Validation, and Test. Across all four metrics, there is a slight decline in scores as the model transitions from the training set to the test set, indicating a small performance drop. However, the overall scores remain high, suggesting that the model is well-trained and generalizes reasonably well to unseen data.

Conclusion

In summary, the helmet detection system offers a comprehensive and automated approach to enforcing helmet regulations. Utilizing YOLOv5 for accurate helmet detection and OCR for Number plate recognition, the model processes real-time traffic footage efficiently. The system identifies violations, calculates fines, and provides an easy-to-use payment system through an integrated gateway. This automation reduces the need for manual traffic enforcement and enhances road safety. By simplifying fine collection and generating receipts digitally, it improves both compliance and record-keeping. Overall, this project showcases how AI can optimize traffic monitoring and create a more effective enforcement mechanism. The system could integrate facial recognition to identify repeat offenders and improve accuracy of detection under various lighting and weather circumstances. Additionally, expanding to detect more traffic violations and enhancing the payment gateway in order to integrate seamlessly with various platforms would streamline the fine payment process.

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