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Original Article

Image Based Helmet Detection Using Deep Neural Networks

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Abstract - *In recent years, road safety has become a significant concern due to the rise in traffic violations and accidents. One of the major causes of fatalities is the non- compliance with helmet usage among two-wheeler riders. This project proposes an AI-powered system for automatic helmet detection to ensure traffic law compliance. The system uses Deep Neural Network (DNN) YOLOv9 models to accurately detect helmet usage. Once a violation is detected—such as a rider without a helmet—the number plate is extracted and processed using a deep learning-based character recognition model. The system operates entirely through an AI-driven software pipeline that analyzes image or video input in real time. It detects riders, verifies helmet usage, localizes number plates, and recognizes registration details. Upon detecting a violation, the system can log the event, store evidence, and trigger automated digital notifications to relevant authorities. This software-based automation minimizes manual effort, enhances detection accuracy, and reduces delays in addressing traffic violations. The proposed solution is scalable and adaptable for deployment in high-traffic environments, contributing significantly to improved road safety and more effective enforcement of traffic regulations.*

Keywords - *Helmet detection, Number plate recognition, Deep learning, Road safety, Traffic monitoring.*

I. INTRODUCTION

The growing number of road accidents and fatalities involving two-wheeler riders has become a pressing concern for traffic management authorities and public safety organizations. Among the most common causes of these accidents is the failure of riders to wear helmets, which are crucial for protecting the head and reducing injury severity during collisions. Despite numerous awareness campaigns and legal mandates, helmet compliance remains inconsistent, especially in densely populated urban areas. This highlights the need for an automated system that can continuously monitor and enforce helmet usage without requiring significant manual intervention.

Traditional methods of traffic monitoring rely heavily on manual surveillance and physical presence of traffic police, which is not only resource-intensive but also prone to human error and inefficiency. These limitations make it difficult to ensure consistent enforcement of traffic rules. There is a critical need for a technological solution that can automate the detection of helmet violations and help in real-time law enforcement. The use of deep learning and computer vision can significantly improve the reliability and speed of detecting violations.

Integrating helmet detection with number plate recognition offers a comprehensive solution to identify and penalize offenders effectively. Once a violation is detected—such as a rider not wearing a helmet—the system can automatically extract the vehicle's registration number, helping authorities take immediate action. This dual capability enables better monitoring of compliance and reduces the dependency on physical checkpoints or random inspections.

Deep Neural Networks (DNN), particularly the YOLO (You Only Look Once) model, have shown remarkable performance in object detection tasks. By leveraging the YOLO9 variant, the system ensures high accuracy and real- time detection speed. This allows for effective surveillance in fast-paced environments, such as highways and busy intersections, where quick decision-making is essential. The model's ability to detect small and fast-moving objects makes it ideal for this application.

Optical Character Recognition (OCR) technology plays a vital role in translating captured number plate images into readable text. When combined with a robust detection framework, OCR can accurately identify vehicle registration numbers even under varying lighting conditions or image distortions. This ensures that violations are logged correctly and with minimal chances of false identification, which is critical for legal follow-up.

To enhance the practicality and implementation scope of the project, the system includes hardware components like Arduino microcontrollers and GSM modules. The Arduino is used to interface with the AI model and coordinate the input/output signals, including camera activation and message transmission. This hardware-software integration ensures a seamless operation and enables real-world deployment of the system in various settings.

The GSM module is utilized to send alert messages or notifications to vehicle owners or enforcement authorities. Upon detecting a helmet violation and recognizing the number plate, a message is automatically generated and transmitted. This automation eliminates the need for manual reporting and enables quicker response times, thereby improving the overall efficiency of traffic rule enforcement.

The proposed system is scalable, meaning it can be implemented in a variety of environments, from small town junctions to large metropolitan areas. It can be integrated with existing traffic surveillance infrastructure or deployed as a standalone system. Its adaptability ensures that different regions with different infrastructural capabilities can benefit from improved traffic regulation and road safety.

Furthermore, the solution reduces the need for continuous human monitoring, allowing traffic personnel to focus on more critical or emergency tasks. Automated monitoring systems can function around the clock without fatigue, ensuring consistent enforcement and minimizing the chances of rule evasion by riders during off-peak hours or in less-monitored areas.

From a societal perspective, this project promotes responsible driving behavior and contributes to public awareness about the importance of helmet usage. As the risk of being caught and fined becomes more certain, riders are more likely to adhere to helmet laws, ultimately leading to a decline in head injury cases and fatalities resulting from two- wheeler accidents.

The system also provides data analytics capabilities by logging the time, location, and frequency of violations. This data can be invaluable to traffic authorities for identifying high-risk areas, planning targeted interventions, and evaluating the effectiveness of traffic safety campaigns over time. In conclusion, the implementation of an image-based helmet detection and number plate recognition system powered by deep neural networks is a forward-thinking step toward enhancing road safety. It offers a practical, efficient, and scalable solution for enforcing helmet laws, reducing accident rates, and promoting a culture of compliance and safety among two-wheeler riders.

II. LITERATURE SURVEY

The study by Arora et al. [1] presents a CNN-based helmet detection system designed to automate traffic monitoring. Using a custom dataset and preprocessing techniques, the model achieves high precision and recall in identifying riders with and without helmets. The system is capable of real-time deployment and reduces the need for manual surveillance, although challenges like poor lighting and occlusion remain. This work highlights the potential of AI in improving road safety and forms a strong foundation for intelligent enforcement systems.

Gupta et al. [2] focus on Automatic Number Plate Recognition (ANPR) by combining CNN for detection and OCR for text extraction. Their system is specifically designed for Indian license plates, addressing variations in font and size. Techniques such as edge detection and binarization enhance recognition accuracy, achieving over 90% performance. The integration of Tesseract OCR and testing on real-time feeds demonstrate its applicability in intelligent transportation systems despite environmental challenges.

Kumar et al. [3] introduce a real-time helmet violation detection system using YOLOv5, emphasizing speed and accuracy. Their model is trained on labeled datasets and deployed in traffic surveillance scenarios. It outperforms earlier YOLO versions and includes mechanisms for violation logging. The study also uses heatmaps to minimize false detections, showcasing the effectiveness of deep learning in dynamic traffic environments.

Zhang et al. [4] propose an integrated system combining helmet detection and number plate recognition using YOLO and OCR. The system processes live traffic video and identifies violations efficiently under varying conditions. It supports scalability and can be linked to centralized databases for automated enforcement. This research demonstrates the advantages of combining multiple AI techniques for smart city applications.

Al-Saadi et al. [5] explore a broader vehicle violation detection framework using CNN and image processing techniques. Their system detects helmet usage and other violations while logging data with timestamps and GPS. It works with both static and mobile cameras and performs reliably in urban conditions. The study emphasizes cost- effective and autonomous traffic monitoring solutions.

Sharma et al. [6] focus on OCR-based number plate recognition tailored for smart cities. Using segmentation, edge detection, and morphological operations, the system extracts and recognizes characters effectively. It achieves over 85%

accuracy and addresses challenges like skewed and low-resolution plates. The study also suggests cloud integration and multi-language support for enhanced scalability.

Singh et al. [7] and Ahmed et al. [8] present comprehensive AI-based traffic monitoring systems. These systems integrate YOLO for detecting violations such as helmet use and seatbelt compliance, along with OCR for plate recognition. They operate in real time, log violations with timestamps, and minimize human intervention. Their scalability and adaptability make them suitable for modern urban traffic management.

Wang et al. [9] and Patel et al. [10] further advance intelligent traffic systems by combining real-time video surveillance, YOLO-based detection, and OCR with cloud storage and analytics. These systems provide automated alerts, data visualization, and flexible deployment on edge devices. Their results demonstrate high accuracy and efficiency, reinforcing the role of AI in developing smart, scalable, and cost-effective road safety solutions.

III. EXISTING SYSTEM

The existing system primarily relies on manual monitoring and traditional CCTV-based surveillance to detect traffic violations. Traffic police manually observe traffic conditions and identify violations, which is highly inefficient, error-prone, and requires extensive manpower. Even with CCTV cameras, the analysis and reporting of violations are often carried out manually, which leads to delays and inefficiencies. Additionally, current systems that perform license plate recognition do not include helmet detection, making them ineffective in ensuring rider compliance with safety regulations. The existing approaches lack real-time processing, making them unsuitable for high- density traffic areas where continuous monitoring is essential. As a result, the current systems are not scalable, have limited accuracy, and often fail to enforce safety laws effectively.

A. Disadvantages of the Existing System

Manual Monitoring Inefficiency

- Existing systems heavily rely on manual surveillance by traffic police, which is time-consuming and prone to human errors.

Delayed Response Time

- Traditional systems rely on post-event analysis, where violation detection happens after the incident, leading to delayed penalty processing.

Lack of Scalability and Accuracy:

- Conventional systems do not scale well in densely populated urban areas.

B. Proposed System

The proposed system leverages deep neural networks to automate helmet detection and number plate recognition in real-time, addressing the limitations of the existing systems. If a violation is detected, the system extracts the number plate from the image and processes it using OCR technology to convert the plate information into text. The recognized vehicle number is then logged into the system for further processing, allowing authorities to issue violation notices. The system operates in real-time, significantly reducing the time required to identify and penalize violators. Furthermore, the automated approach eliminates human errors and enhances the accuracy of violation detection. The proposed system is capable of handling large amounts of data from multiple camera feeds, making it highly scalable and suitable for deployment in urban environments with dense traffic. By integrating advanced deep learning techniques, the system provides a robust and efficient solution for ensuring helmet compliance and improving road safety.

IV. SYSTEM ARCHITECTURE

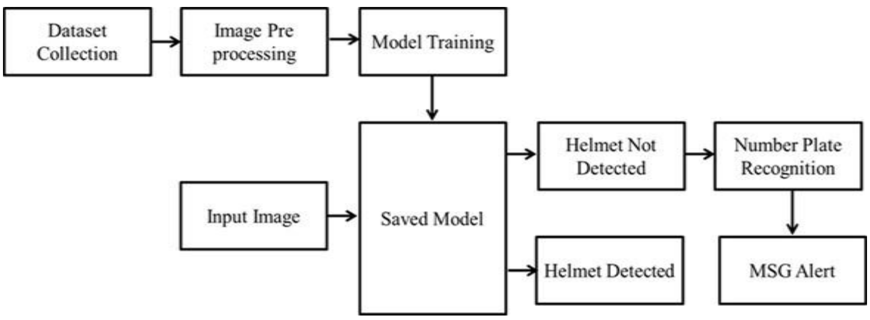

Figure 1: System Architecture

Dataset Collection: The process begins with gathering image data of two-wheeler riders, both with and without helmets, to train the model.

Image Preprocessing: These collected images undergo preprocessing steps such as resizing, normalization, and augmentation to prepare them for effective model training.

Model Training: A deep learning model, typically a YOLO variant, is trained on the preprocessed dataset to distinguish between helmeted and non-helmeted riders.

Saved Model: After training, the model is saved and becomes the central processing unit for inference. It takes input images and classifies them.

Input Image: During real-world deployment, new images from traffic surveillance cameras are fed into the saved model.

Helmet Detected / Not Detected: The model analyzes the image. If a helmet is detected, no further action is taken. If no helmet is detected, it triggers the next step.

Number Plate Recognition: For violations, the system extracts the vehicle's number plate from the image using OCR techniques.

MSG Alert: Once the number plate is recognized, a GSM module sends an automated message alert to the concerned authority or vehicle owner, notifying them of the violation.

A. YOLO Algorithm

As of now (April 2025), YOLO9 refers to the latest evolution of the "You Only Look Once" (YOLO) family of real-time object detection algorithms, designed to offer even faster, more accurate, and more efficient detection than its predecessors.YOLO9 builds upon the innovations introduced in earlier versions like YOLOv8, integrating cutting-edge improvements such as enhanced Transformer- based backbones, dynamic label assignment, and multi-scale feature fusion for superior detection of small, medium, and large objects. It utilizes a highly optimized architecture that balances computational speed and detection precision, making it ideal for real-time applications across edge devices, mobile platforms, and cloud systems. YOLO9 also focuses on modularity and flexibility, allowing easy customization for different tasks like instance segmentation, object tracking, and pose estimation. Key improvements include better anchor-free detection heads, advanced data augmentation techniques like Auto Augment v2, and support for large-scale training with distributed systems, resulting in state-of-the-art performance on benchmarks like COCO and Open Images datasets.

B. Block Diagram

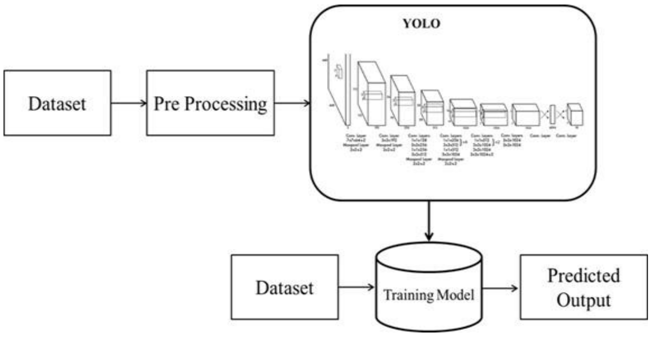

Figure 2. Proposed Architecture

Data Collection and Pre-processing:

- This module is responsible for gathering transformer images from various sources, including real-world images and publicly available datasets.
- The collected images are annotated with fault labels such as oil leakage, overheating, and bushing damage.
- Preprocessing steps include image resizing, normalization, and augmentation to improve model robustness and generalization.

YOLO Model Training:

- In this module, the YOLO deep learning model is trained using the pre-processed dataset.
- The model is fine-tuned using hyperparameter optimization, ensuring it accurately detects and classifies different transformer faults.
- The training process involves multiple iterations to enhance model performance and minimize false positives.

Fault Detection and Monitoring:

- When a fault is detected, alerts are generated to notify maintenance teams for immediate action.

Performance Evaluation and Validation:

- The final module evaluates the performance of the fault detection system using accuracy, precision.
- The system undergoes extensive validation against real-world scenarios to ensure its reliability and effectiveness in identifying transformer faults.
- The evaluation results help refine the model for improved fault detection accuracy.

C. Flow Diagram

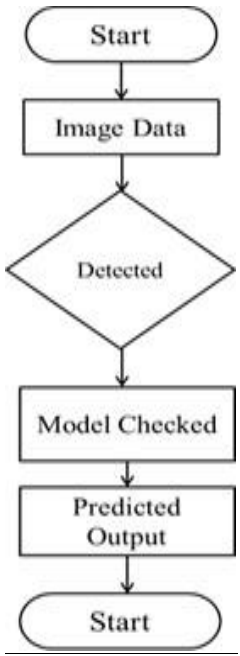

Figure 3: Flow Diagram

The flowchart represents a simple image processing and detection pipeline. It begins with the Start stage, followed by Image Data acquisition where input images are captured or loaded into the system. The process then moves to a Detection step, where the system checks whether relevant objects (such as helmets or number plates) are identified in the image. Once detection is confirmed, the workflow proceeds to Model Checked, where the trained deep learning model analyzes the detected features. After processing, the system generates the Predicted Output, which may include classification results or identified objects. Finally, the process loops back to the start, indicating continuous or real-time operation of the system.

V. OPTICAL CHARACTER RECOGNITION (OCR)

A. Theory

Tesseract is an open-source Optical Character Recognition (OCR) engine initially developed by Hewlett- Packard and later maintained by Google. It converts printed, handwritten, or scanned image text into machine-encoded text. It works best with high-resolution, clean documents and supports over 100 languages.

The core theory of Tesseract lies in pattern recognition and machine learning. It uses LSTM-based deep learning models (since version 4.0) to identify characters and words in complex documents, making it significantly more accurate in dealing with skewed, noisy, or varied-font input data.

B. Working

Tesseract OCR operates in several stages:

1. Image Acquisition: Input image is loaded using OpenCV or PIL.
2. Preprocessing: Optional step to improve OCR accuracy using thresholding, denoising, or edge enhancement.
3. Page Layout Analysis:
   - Detects blocks, lines, and words.
   - Identifies orientation and script.
4. Line and Word Recognition:
   - Uses LSTM (Long Short-Term Memory) models to recognize characters.

- Performs segmentation, character prediction, and language modeling.

5. Post-Processing:
   - Applies dictionary-based spell-checking and context understanding.
6. Output:
   - Text can be output in .txt, .pdf, or .hocr formats.

VI. RESULTS AND DISSUSSION

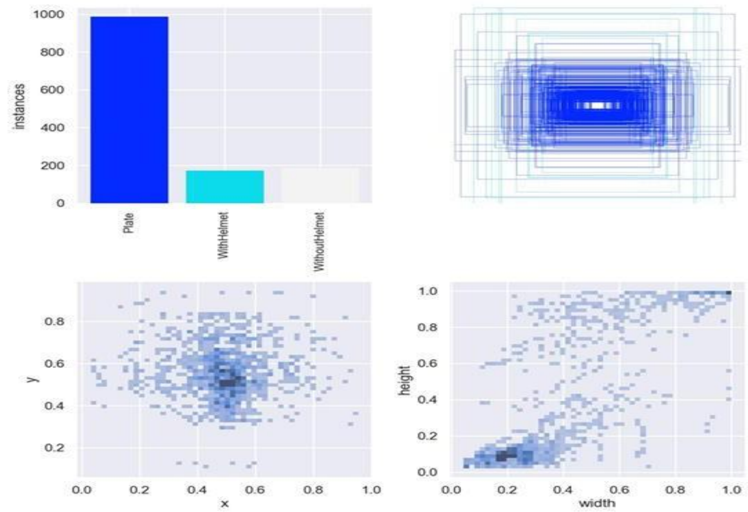

Figure 4: Class Instances

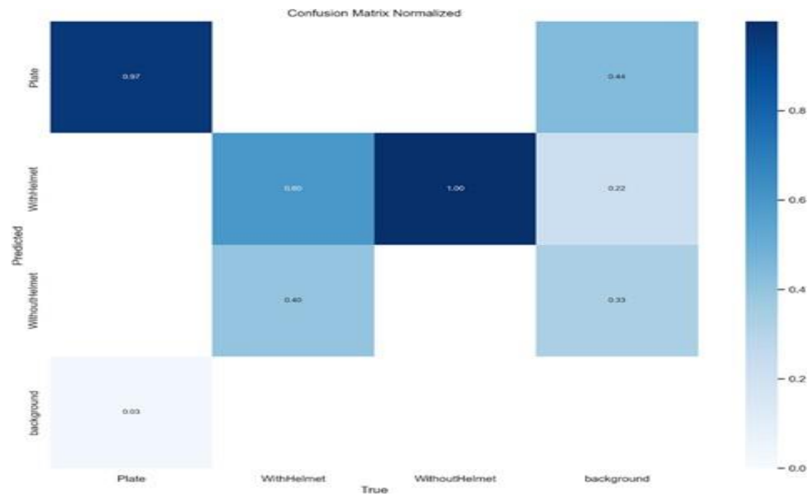

Figure 5: Confussion Matrix

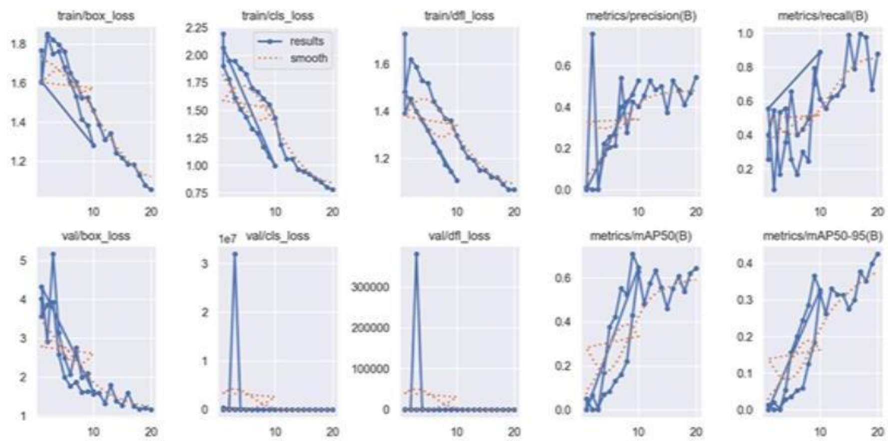

Figure 6: Metric of yolo trained model Output

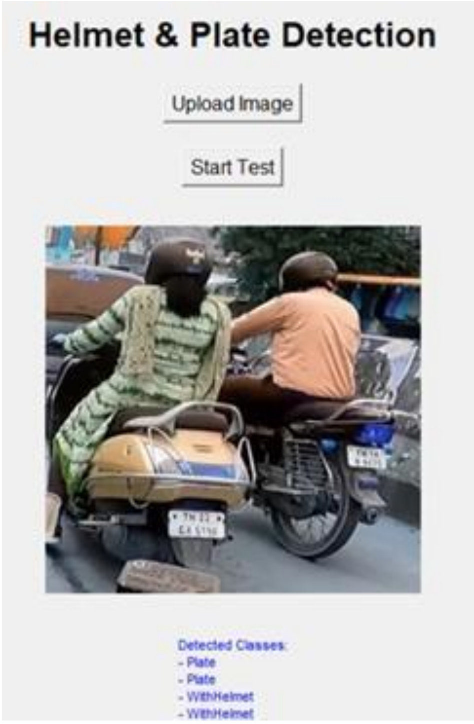

Figure 7: Helmet and Plate Detection

Figure 8: Number Plate

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Detected: Plate
[INFO] Saved cropped image to output_crop\Plate_1.jpg
OCR Plate Text: TN (2 -
BJ 8057
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Figure 9: Number Plate – OCR – Print

VII. CONCLUSION

In conclusion, the Image-Based Helmet Detection and Number Plate Recognition system using Deep Neural Networks presents an innovative and efficient approach to enhancing road safety and enforcing traffic regulations. By leveraging advanced AI models like YOLO for real-time helmet detection and Optical Character Recognition (OCR) for number plate identification, the system automates the monitoring of two-wheeler riders with high accuracy. This reduces the reliance on manual surveillance, minimizes human error, and accelerates the process of law enforcement. The solution is cost-effective, scalable, and suitable for deployment in urban areas, highways, and even private industrial premises. Overall, the project contributes significantly to promoting safe driving practices and reducing accident-related fatalities, making it a valuable addition to intelligent traffic management systems.

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