Deep Learning-based Approach for Detecting Traffic Violations Involving No Helmet Use and Wrong Cycle Lane Usage

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ABSTRACT

Road safety is put at risk by violations of traffic rules including riding a motorcycle without a helmet and using cycle lanes improperly. A deep learning-based framework for the automated real-time identification of these violations is presented in this research. The suggested system uses advanced object detection and tracking algorithms in conjunction with spatial reasoning to detect bicycles riding outside of approved cycle lanes and motorcyclists without helmets. To improve detection accuracy, the system uses bounding box modifications, centroid-based relationship, and region-specific filtering. Additional elements, such as speed and directional analysis, add context to the observed violations.In addition to providing visual feedback and keeping track of cumulative counts, the system performs excellently in identifying and reporting violations. The architecture is flexible and can be expanded to handle a wider range of traffic violations. It is made to function smoothly in a variety of urban traffic situations. The suggested technique reduces dependence on manual monitoring by automating violation identification, and thus helps traffic management authorities improve road safety. In order to verify and improve the system, future development will concentrate on increasing functionality, enhancing edge device efficiency, and carrying out realistic deployments.

Keywords

Computer Vision, Traffic Surveillance, YOLO, Vehicle Speed Detection, Direction Detection, Helmet Detection, Lane Violation, Non-ANPR Cameras

1. INTRODUCTION

As urbanization grows and the use of private vehicles increases, cities face additional traffic management and road safety concerns. Wearing a motorbike helmet and encroaching on cycles by unlicensed vehicles (others) are just the beginnings of these challenges. These infractions not only disrupt the planned operation of urban infrastructures, but they also have serious implications for public safety, necessitating active monitoring and punishment.

Traditionally, violations were dealt with manually or using specialized technologies such as automatic number plate recognition cameras and other specific gear. Though such systems can produce reliable results, their high cost and infrastructure requirements make them unsuitable for many applications, particularly those with limited budgets. As a result, there is a greater need for more basic and expandable solutions that can be integrated into current urban infrastructure.

Recent developments in computer vision [7] and deep learning have created new opportunities to use general-purpose security cameras to solve problems. Being frequently placed for general surveillance or security purposes, such cameras provide a good opportunity to monitor traffic behavior on a broader scale without incurring additional hardware costs. The integration of several cutting-edge machine-learning techniques with current video networks now allows for the automated detection of specific traffic offenses at minimal expense.

The research presented here provides a deep learning-based method for detecting two common traffic violations: cycling without a helmet and non-cyclists encroaching on bike lanes. The framework recognizes multiple things in real-time using powerful object detection techniques like YOLO (you only look once), as well as tracking and contextual analysis to highlight infractions. The desired solution is an automated large-scale system that promotes greater road safety and the importance of following traffic laws.

Traditionally, violations have been dealt with either manually, or with special systems such as automatic number plate recognition cameras and other customized hardware. Though such systems can produce accurate results, their cost and infrastructure requirements render them incapable of being used in many a place, especially under budget constraints. Hence arises the need for more simple and expandable solutions that could be built into the existing urban infrastructure itself.

1.1 Motivation

This study is motivated by a desire to improve traffic safety, expand regulation coverage, and use existing resources better. Cities can adapt general-purpose surveillance cameras into intelligent systems that detect specific traffic offenses.

(1) Monitor more places without the need for pricey, specialist equipment.
(2) Increase the frequency and consistency of monitoring, resulting in a higher commitment to traffic laws.
(3) Integrate the solution with current smart city frameworks and data analytics platforms to improve urban traffic management.

1.2 Contributions

The primary contributions of work in this paper are:

(1) **Utilizing Public Cameras**: Proving the effectiveness of using general-purpose surveillance cameras—which are frequently placed for security or general monitoring purposes—instead of specialist equipment to detect helmet violations and improper cycling lane usage.
(2) **Improved Tracking and identification**: Motorcycles, bicycles, and other vehicles can be identified using YOLO-based object identification models. These detections are then combined with reliable tracking methods that maintain item identities across several frames.
(3) **Helmet Detection Framework:** Presents a customized method that uses high-accuracy deep learning models to determine if motorcycle riders are wearing helmets.
(4) **Cycle Lane Misuse Detection**: Developing a strategy that combines environmental analysis of lane-specific areas with object classification to detect illegal automobiles in bicycle lanes.
(5) **Adaptable and Scalable System**: Designing a modular framework that can be easily modified for varied camera viewpoints and urban environments, as well as integrating into cloud-based systems for large-scale implementations.

2. RELATED WORK

Several studies have examined helmet violation detection systems that use deep learning approaches for smart handling of traffic. A modified version of PerspectiveNet, which uses EfficientNet v2 as a base for feature extraction, has been proposed to detect helmet violations with less computing complexity [1]. Another technique uses Faster R-CNN to process real-time video streams, detecting helmet violations and linking them to Intelligent Transportation Systems (ITS) [2]. Furthermore, YOLOv8 paired with OCR has been used to detect motorcycle riders without helmets and extract license plate information from real-time video footage. This method uses a specific dataset for Indian license plates to correct errors in plate designs through CNN-based training [3].

These approaches show progress in using deep learning for traffic monitoring and rule enforcement.

3. METHODOLOGY

The proposed framework comprises several key components: data acquisition, object detection, multi-object tracking, helmet detection, vehicle type detection, and violation flagging.

3.1 Data Acquisition

The dataset for this project was collected from real-world CCTV footage. These video streams were collected from surveillance systems that monitor public roadways and bicycle lanes.

Pre-trained YOLO models were refined using a carefully selected dataset of CCTV footage to ensure precise and trustworthy objects recognition. Fine-tuning takes advantage of pre-trained models' wide feature extraction capabilities while customizing them to the particular needs of the target task.

A total of 400 publicly accessible cameras were available with a complete raw feed of 6 months with 24 hours complete feed for each day, thus total hours accounting to be more than 1728000 hours.

3.2 YOLO Model Architecture

The YOLO (You Only Look Once) model is a real-time object detection framework known for its speed and accuracy. Unlike traditional methods that involve region proposal followed by classification, YOLO treats object detection as a single regression problem. It divides the input image into a grid and predicts bounding boxes, class probabilities, and confidence scores for each cell.

Key Components of the YOLO Architecture:

(1) **Input Layer:** Resizes the image to a fixed dimension and normalizes pixel values.
(2) **Feature Extraction:** A series of convolutional layers extract features from the image, with batch normalization and pooling layers to improve generalization and reduce overfitting.
(3) **Grid-based Prediction:** The image is divided into an $S \times S$ grid. Each cell predicts bounding boxes, objectness scores, and class probabilities.
(4) **Bounding Box Regression:** Each bounding box is defined by its center coordinates, width, height, and confidence score, indicating the probability of the box containing an object.
(5) **Non-Maximum Suppression (NMS):** Filters overlapping boxes to retain the most probable detection for each object.

YOLO's unified architecture makes it exceptionally fast, making it suitable for real-time applications like traffic monitoring. Its trade-off between speed and accuracy allows scalable deployment on edge devices or cloud platforms.

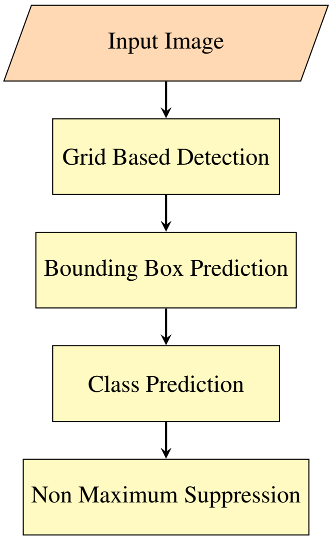
For further details, refer to the article "Computer Vision and Deep Learning based Approach for Traffic Violations due to Overspeeding and Wrong Direction Detection"

3.3 Model Architecture and Discussion

The system utilizes a modular deep-learning pipeline for real-time detection and tracking of traffic violations. A YOLO-based [4] architecture was employed to identify vehicles, cyclists, and pedestrians, leveraging its capability for fast, single-pass detection.

Rule-based logic and spatial algorithms are then applied for specific violation checks such as no helmet detection and wrong cycle lane usage.

Step-wise YOLO [4] Model Process:



Output: Detection of objects (motorcycles, bicycles, heads) with bounding boxes, class labels, and confidence scores.

We utilized the YOLO Model for object identification and localization and integrated a tracking mechanism to maintain consistent object identities across frames. The following subsections elaborate on key components of the system:

(1) **Object Detection and Object Tracking :** A pre-trained YOLO model is used for object detection and tracking.
  (a) **Object Detection :** YOLO divides the image into an $S \times S$ grids. Each grid cell predicts bounding boxes and class probabilities for objects whose centroids lie within the cell. Each prediction includes:
    i. Bounding box coordinates (x, y, w, h)
    ii. Object confidence score
    iii. Class probabilities
  The confidence score is computed as:
  $$\text{Confidence} = P(\text{Object}) \cdot \text{IOU}_{\text{Pred,True}}$$
  where $P(\text{Object})$ indicates the probability of an object in the cell, and $\text{IOU}_{\text{Pred,True}}$ is the intersection-over-union of the predicted and true bounding boxes.
  (b) **Object Tracking :** To maintain object consistency across frames, a tracker assigns unique IDs to each detected object. Using features such as centroids and bounding box dimensions, the tracker establishes the correspondence between detections in consecutive frames.

(2) **Centroid [5] Calculation and Categorization:** Once an object is detected, we calculate its centroid:
$$\text{centroid}_x = \frac{x_1 + x_2}{2}, \quad \text{centroid}_y = \frac{y_1 + y_2}{2}.$$
This geometric center simplifies spatial representation and is crucial for subsequent analyses like helmet detection and lane verification.
Detected objects are then grouped into certain categories (e.g., motorcycles, bicycles, pedestrians), allowing the framework to use specialized logic for violation detection.

(3) **No Helmet Detection Process:** To identify no-helmet violations, the system focuses on detected motorcycles and nearby pedestrians:

  (a) **Motorcycle Bounding Box Adjustment:** The bounding box for motorcycles is dynamically adjusted to include the rider's potential head region. The height of the bounding box is extended by 90%, and its top boundary is elevated accordingly.

  height = int(height * 1.90)

  y1 = max(int(y1 - (height * 0.90)), 0)

  where y1 is the coordinate of the upper line of the bounding box. This ensures that we captures the rider's upper body for the "No Helmet" check.

  (b) **Person-Centroid Matching:** Pedestrian centroids are checked against the extended motorcycle bounding box. If a pedestrian's centroid lies within the bounding box, they are considered as the motorcycle rider.

  (c) **Helmet Status Check:** A secondary classifier or a rule-based condition checks whether the detected pedestrian has a helmet. In cases where no helmet is detected, the system flags the violation.

Additionally, any pedestrian centroids detected outside a motorcycle bounding box but still within the monitored road region are flagged as "No Helmet Outside Motorcycle," ensuring comprehensive helmet compliance detection.

(4) **Avoiding Detections of Persons on Foot or on a Bicycle:**

  (a) The logic only applies the above "no helmet" check when the bounding box is classified as a motorcycle.

  (b) For pedestrians (not inside a motorcycle bounding box) or for cyclists (class 1 if it's a bicycle, but specifically handled differently in the program), the "no helmet" violation is not triggered.

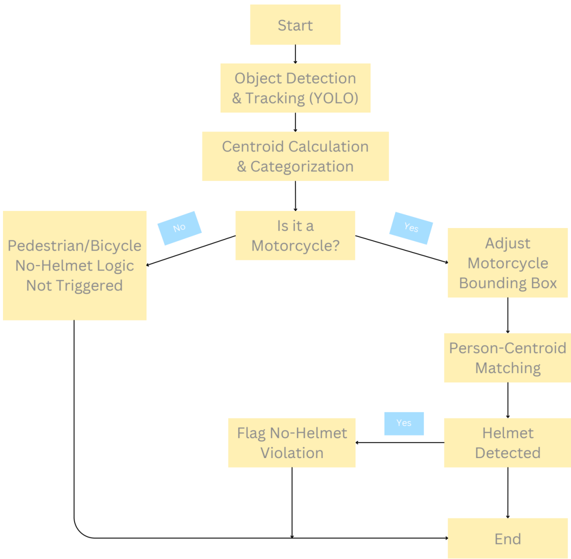


Fig 1. Step wise chart for No Helmet violations Detection

(5) **Wrong Cycle Lane Detection:** For cycle lane violations, the system leverages spatial mapping and vehicle classification:

  (a) **Cycle Lane Region Identification:** The cycle lane is pre-defined as a polygonal region using its coordinates.

  (b) **Violation Detection:** A bicycle outside the cycle lane is flagged as ”Wrong Lane” with a magenta bounding box. Other vehicles (e.g., motorcycles or four-wheelers) within the cycle lane are similarly flagged as intruders.

3.4 Visualization and Output:

The suggested system provides real-time visualization and output to help recognize traffic violations. For each processed frame, the system overlays:

(1) Bounding boxes around detected heads without a helmet

(2) Labels including vehicle type and track ID

(3) Bicycles detected in the wrong cycle lanes are highlighted and labeled

(4) Both no helmet and wrong lane violations are displayed with real-time violation counts on the top-left corner of the screen

This architecture offers an effective, real-time solution for detecting no helmet wear and wrong cycle lane usage, ensuring scalability and flexibility under varying traffic conditions.

Below are the visualizations including the bounding box for No-Helmet and Wrong lane violation-

Fig 2. Yellow Bounding Box for violations due to not wearing a helmet

Fig 3. Yellow Bounding Box for violations due to not wearing a helmet

Fig 4. Yellow Bounding Box for violations due to not wearing a helmet

Fig 5. Yellow Bounding Box for violations due to not wearing a helmet

Fig 6. Pink Bounding Box for violations due to Wrong lane movement

4. CONCLUSION AND FUTURE WORK

The proposed deep learning-based approach successfully detects two key real-time traffic violations: no helmet worn by motorcyclists and incorrect cycle lane usage by bicycles. The framework guarantees excellent accuracy in identifying and flagging violations within predefined zones by using centroid-based association algorithms and region-specific filtering. The results show that the system can efficiently identify violators, provide visual feedback, and track cumulative violations. In addition to improving road safety, the suggested solution establishes the framework for future scalable applications in intelligent transportation systems.

The framework also lowers the need for manual traffic monitoring by automating violations identification and providing actionable data to traffic management authorities. This will lower the dependence on manual traffic monitoring by automating the process.

Although the current implementation offers a complete solution for identifying violations such as improper bicycle lane usage and helmet use, there are various opportunities for future improvement :

(1) Deploying the technique across many cameras with integrated tracking capabilities would provide better surveillance of larger traffic zones and improve tracking consistency.
(2) Including specific helmet detection models, possibly employing fine-grained image analysis, could enhance accuracy in differentiating helmets from other headgear, especially in challenging settings such as low light or partial vision.
(3) Integrating Automatic Number Plate Recognition (ANPR) with traffic databases can significantly enhance traffic management systems by automatically generating violation reports and issuing fines, streamlining enforcement processes by reducing manual intervention.
(4) In addition to static violations, the system might examine trends like careless driving or risky overtaking techniques, offering a deeper understanding of traffic safety concerns.

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