Computer Vision and Deep Learning based Approach for Violations due to Illegal Parking Detection

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ABSTRACT

Illegal parking [9] in cities is a critical problem in urban traffic management, pedestrian safety, and visual appeal. Conventional mechanisms are reliant on the visual monitoring capabilities of law enforcement officers and citizen complaints that are expensive and time-delayed. In the recent past, the availability of public camera infrastructure and research in object detection using deep learning enabled the development of real-time, automated mechanisms for enforcing parking regulations. In this paper, a novel methodology is proposed that utilizes publicly available camera feeds, the most advanced object detection models, and a spatial analysis based on polygon detection to identify and flag illegally parked vehicles. By modeling restricted zones as polygons within the camera's field of view and by integrating a temporal persistence criterion, the approach in this paper correctly identifies vehicles that remain stationary in no-parking areas beyond some pre-defined threshold, discarding false positives along the way. It will be shown that the pipeline is scalable and robust for large-scale deployments through continuous video tracking and YOLO-based detection. It indicates a promising direction toward smart city initiatives that may enable automated and proactive detection of traffic violations.

Keywords

Computer Vision, Traffic Surveillance, YOLO, Illegal parking detection, YOLO object detection, Multi-object tracking, Public CCTV monitoring, Polygon-based spatial analysis, Automated traffic enforcement, Temporal violation criteria, Real-time video analytics

1. INTRODUCTION

Illegal parking persists as one of the leading issues in modern metropolitan areas, thus causing a considerable proportion of traffic jam congestion, poor pedestrian flow, and road hazards. In line with the increasingly complex metropolitan conditions, efficient and scalable ways to mitigate traffic violations become a problem of city authorities and planners. Traditionally, approaches tend to involve manual observation by traffic wardens or reporting from citizens, and they are always time-consuming, leading to delayed response times. These problems can be greatly relieved by using camera feeds in real time from autonomous and intelligent systems to monitor critical junctions for violations without human intervention.

Recent advances in computer vision and deep learning, especially in object detection and multi-object tracking, have now made it possible to track vehicles and their spatiotemporal patterns with much precision. Existing public camera infrastructures, already found in major cities, can be utilized for this task, thus avoiding additional costs of installation. Based on this, a new method is proposed that uses available pre-trained object detection YOLO models, polygonal defined zones, and frame-based time analysis to detect and raise flags for vehicles illegally parked. The strategy in this paper is the powerful synergy of deep, robust models combined with the geometric constraints provided by pre-defined polygons that can offer scalability and accuracy under environmental conditions.

1.1 Contributions

The proposed methodology extends beyond academic or theoretical contexts to offer tangible benefits for urban governance, transportation management, and public safety. Its primary real-life contributions include:

(1) **Enhanced Traffic Enforcement Efficiency**: It helps in the real-time identification of illegal parking violations, hence allowing city authorities to immediately identify and take necessary steps against them. It will reduce reliance on manual inspection, thus freeing law enforcement personnel to do their tasks more efficiently. In doing so, it deals with traffic violations much quicker and in a consistent manner, which, in turn improves compliance and minimizes congestion.
(2) **Cost-Effective Infrastructure Utilization**: Leveraging existing public surveillance cameras obviates the need for costly,

specialized hardware. Municipalities can capitalize on their current camera networks, transforming them into intelligent sensors capable of monitoring multiple zones simultaneously. This approach significantly lowers the barrier to large-scale deployment and scaling of enforcement coverage across various neighborhoods

(3) **Increased Transparency and Accountability**: Automated detection systems offer objective, time-stamped evidence of infractions. Such transparency not only increases the credibility of enforcement measures but also deters would-be violators who are aware that their activities might be recorded and reviewed. With time, this will enhance a sense of accountability in road users, making community trust in traffic management policies higher.

(4) **Data-Driven Urban Planning and Policy Making**: Continuous, dependable data on illegal parking tendencies can help in more impactful urban planning. Policy implementers can analyze patterns of non-compliance, focus on areas of high-risk, and adjust infrastructure-from signage, road layouts to recalibration of parking policies-through real-time insights into the same. Moreover, the data generated by this system can be integrated into existing smart city analytics, which would drive informed decisions and policy interventions.

(5) **Improved Quality of Life and Safety** : Reduced cases of illegal parking are more likely to keep the roads, sidewalks, and critical junctions accessible and safe. Emergency vehicles spend less time in delay; pedestrians have fewer obstructions, and commercial activities can flourish in more orderly and predictable transportation environments. Taken together, these improvements enrich the quality of life: safer, more efficient, and more livable urban spaces.

In all, the deployment of the proposed system in real-world scenarios serves as a catalyst for smarter traffic enforcement, more informed policy decisions, and improved societal welfare.

2. RELATED WORK

Many researches covered automated parking and traffic violation detection through computer vision. Early methods were based on background subtraction and motion estimation for the detection of parked vehicles [1]. Nevertheless, these methods were unreliable in dynamic lighting conditions and complex urban scenes. Later, the development of convolutional neural networks (CNNs) brought object detection systems such as Faster R-CNN [2], YOLO [3], and SSD [4] that improved detection accuracy and speed. More recently, YOLOv8 and other fine-tuned models have outperformed their precursors in terms of efficiency and real-time feasibility.

To curb illegal parking, researchers have utilized scene-specific approaches like defining forbidden zones and geometric constraints to classify vehicles as illegally parked if they remain in such zones for a long time [5]. This techniques use the multi-object tracking frameworks such as DeepSORT [6], to retain the consistency of identity along frames. Contrary to the previously published work where environments might be controlled, this approach takes advantage of available CCTV infrastructure and re-tailors the pipeline for ordinary urban junction scenes, hence allowing for realistic deployment scenarios.
During the detection of violation due to illegal parking it is important that vehicles which are at stop due to red or yellow traffic signal are also considered, for which vehicles in illegal parking while signal is green or the vehicle is in the given parking for a long time are flagged.

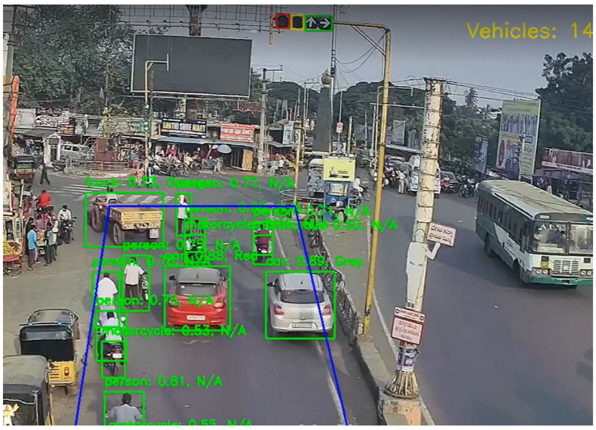

Fig 1. Here the green signal is present with vehicle count in top right corner

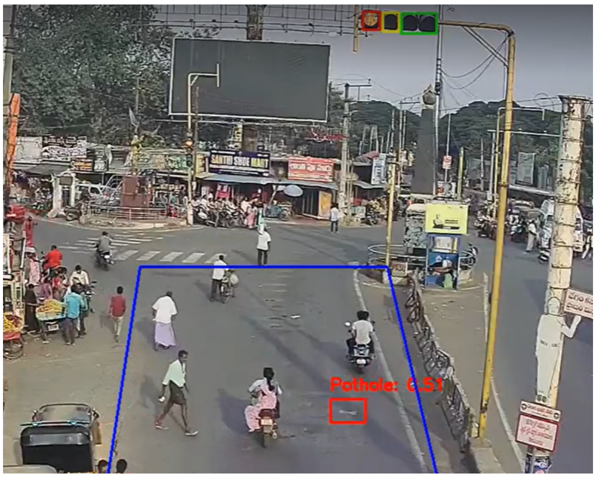

Fig 2. Here the red signal is present with vehicle count in top right corner

3. METHODOLOGY

The proposed methodology is designed to operate autonomously on live camera feeds from public infrastructure, detecting illegal parking events by integrating object detection, polygon-based spatial filtering, and temporal persistence checks.

3.1 Overview

The architecture consists of three main components:

(1) **Data Acquisition:** This approach assumes existing public camera feeds. Videos may be accessed via network streams or downloaded from cloud storage systems. The camera's intrinsic and extrinsic parameters are not strictly required, as the methodology relies on 2D image-plane polygons rather than explicit world coordinates

(2) **Object Detection and Tracking:** Using YOLO-based models, the system detects vehicles frame-by-frame, assigns unique IDs to each tracked vehicle, and records spatial coordinates over time

(3) **Polygon-Based Violation Checking:** Predefined polygons corresponding to restricted (no-parking) zones are applied to the detection results. Vehicles that remain within these polygons beyond a defined temporal threshold are flagged as illegally parked.

3.2 YOLO (You Only Look Once) Architecture

YOLO is a family of one-stage object detectors that predicts bounding boxes and class probabilities directly from full images in a single inference pass. Unlike two-stage detectors, which first generate region proposals and then classify them, YOLO treats detection as a single regression problem.

3.2.1 ***Input and Feature Extraction***. Given an input image $I \in R^{H \times W \times 3}$, where H and W represent the height and width of the frame, YOLO uses a deep convolutional neural network (CNN) to learn feature representations $\phi(I)$ that capture both spatial and semantic attributes of objects in the scene.

3.2.2 ***Grid Division***. YOLO divides the image into an $S \times S$ grid. Each grid cell is responsible for detecting objects whose center falls within that cell.

3.2.3 ***Bounding Box Predictions***. For each grid cell, YOLO predicts B bounding boxes. Each bounding box is defined by four parameters (x, y, w, h) and is accompanied by a confidence score. Formally, YOLO outputs a tensor:

$$Y = \{\hat{b}_{ijb}, \hat{c}_{ijb}, \hat{p}_{ij}\} \quad \text{for } i, j \in \{1, \dots, S\}, b \in \{1, \dots, B\},$$

where $\hat{b}_{ijb} = (x_{ijb}, y_{ijb}, w_{ijb}, h_{ijb})$ are the bounding box coordinates relative to the cell (i, j), $\hat{c}_{ijb}$ is the confidence score, and $\hat{p}_{ij}$ is a set of class probabilities.

3.2.4 ***Post-processing and Filtering***. After obtaining the set of predictions, Non-Maximum Suppression (NMS) is applied to remove redundant boxes and retain only the highest-confidence detections. The final set of detections for each frame t can be represented as:

$$D_t = \{(b_k, c_k) \mid k = 1, \dots, K_t\},$$

where $b_k = (x_k, y_k, w_k, h_k)$ is a bounding box, c_k its associated class, and K_t the number of detections in frame t.

3.3 Multi-Object Tracking

After detection, each object must be tracked across frames to ensure continuity of identity and to measure temporal behavior. A common approach is to use motion models and data association techniques.

Motion Models and State Representation
Each tracked vehicle v is represented by a state vector:

$$\mathbf{s}_v(t) = [x(t), y(t), \dot{x}(t), \dot{y}(t)],$$

where $(x(t), y(t))$ denotes the centroid of the vehicle's bounding box at frame t, and $\dot{x}(t), \dot{y}(t)$ represent velocities.

3.4 Model Architecture and Discussion

Now using the YOLO Model various classes of vehicles are detected and are classified into motorcycles, cars etc. Next point-in-polygon test (Geometrical Check) is employed to determine if a vehicle is within a certain polygonal region (eg. a parking zone).
The centroid (C_x, C_y) of a vehicles bounding box is checked against a polygon defined by a set of points $[(X_1, Y_1), (X_2, Y_2), ..., (X_n, Y_n)]$. The pointPolygonTest functionality of OpenCV is used to find if P is a polygon and Q = (C_x, C_y) is a point:

(1) $result > 0$: Q is inside the polygon.

(2) $result = 0$: Q is exactly on an edge of the polygon.

(3) $result < 0$: Q is outside the polygon.

If a vehicle's centroid lies inside the polygon, it is considered "within a designated area" (eg. a parking spot)

Time-Based Violation (Illegal Parking): Once a vehicle is detected inside a polygonal region (e.g., a parking area or restricted zone), the system starts tracking how long it remains there. Each frame increments a counter for that vehicle inside the region.
The above can be formulated as:

$$\text{frames\_inside} = \text{frame\_count} - \text{frame\_initial}$$

- **frames_inside**: Number of frames the vehicle was inside a polygonal region
- **frame_count**: Current frame number
- **frame_initial**: Initial frame number when the vehicle entered the polygonal region

If this duration exceeds a certain threshold required_frames:

$$\text{frames\_inside} \geq \text{required\_frames} \implies \text{ILLEGAL PARKING}$$

Essentially, if a vehicle stays beyond a permissible time without leaving the polygonal zone, it's marked as an illegally parked vehicle.

3.5 Visualization and Output:

For each of the frames that are processed through the model pipeline, the model outputs the following:

(1) A Bounding Box around the detected vehicle along with the vehicle type and the tracking ID of the vehicle

(2) Number of Illegal Parking violations in the given camera feed.

(3) The different colored bounding box around the vehicle in-case of a violation in regards to illegal parking

This outputs helps authorities in finding the vehicles violating the rules.

Below are the 3 consecutive frames taken from a camera which showcase the 3-wheeler vehicle being parked illegally. The red cross shows the centroid which is being tracked in each coming frame to check if the vehicle is still at the same point. The following flagging for illegal parking is only done while the signal is green and during red light, vehicle density is tracked for further processing by authorities.

Fig 3. Blue Bounding Box to flag vehicles parked illegally Frame 1

Fig 4. Blue Bounding Box to flag vehicles parked illegally Frame 2

Fig 5. Blue Bounding Box to flag vehicles parked illegally Frame 3

In all the above frames, it was observed that the centroid is staying stationary in consecutive frames and 3-wheeler vehicle is being parked illegally in continuous frames.

4. CONCLUSION AND FUTURE WORK

In this paper, a deterministic automated, camera-based system is presented that detects and flags illegally parked vehicles in urban environments. By combining publicly available CCTV feeds, state-of-the-art YOLO-based object detection, and polygon-based geometric constraints, this approach reliably identifies vehicles parked in restricted zones and enforces temporal thresholds to reduce false alarms. This method relies on multi-object tracking for maintaining consistent identities over time, thus ensuring robust detection even in dynamic and cluttered scenes. The combination of off-the-shelf deep learning models with flexible spatial representations, such as polygons, enables straightforward scalability and adaptation to varying camera perspectives, environmental conditions, and region-specific parking policies. The proposed solution therefore offers a resource-efficient and cost-effective enhancement to the current traffic enforcement measures that would promote transparency, accountability, and data-driven decision-making within city management frameworks. The experiments indicated that these system holds promise for large-scale, real-time deployments, ultimately contributing to safer, more orderly urban areas.

While the proposed system effectively addresses key challenges in automated illegal parking detection, several avenues exist for further refinement and expansion:

(1) **Integration with Vehicle Classification and License Plate Recognition:** By integrating technologies like license plate recognition (LPR) or vehicle make-and-model identification, the enforcement process could be made more efficient and transparent. This would allow authorities to automatically link parking violations to specific vehicles, speeding up the process of issuing fines, legal actions, and notifications.

(2) **Adaptive Thresholding and Dynamic Policy Adjustments:** Right now, the system uses fixed time limits for detecting violations. However, future updates could use more flexible, adaptive thresholds that adjust parking rules based on factors like location-specific regulations, ongoing events, or changing demand for parking. This would make the system more responsive and fair.

(3) **Integration of Additional Contextual Data:** In the future, the system could consider additional data, such as weather conditions, traffic flow, or pedestrian activity. By understanding how these factors relate to illegal parking, policymakers can develop more targeted solutions to address the root causes of the problem.

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