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Park-Alert: AI-Assisted Parking Management System

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Abstract: Unauthorized parking in restricted urban zones disrupts traffic flow and burdens manual enforcement. This paper presents PARK-ALERT, a web-based automated no-parking surveillance and violation management system. The platform integrates a browser frontend, a Python Flask backend, and an SQLite database. Vehicles are tracked inside a user-defined four-point Region of Interest (ROI) polygon to measure stationary dwell time. At a 20-second dwell threshold, background plate recognition checks candidates against registered vehicles and dispatches warning notices. Vehicles remaining parked for 30 seconds or more are recorded with time-based fines. Missing, blurry, or unreadable plates trigger officer alerts and are routed into a verification queue. Officers can enter plates manually, add remarks, log audits, manage unpaid and paid challans, and settle penalties. The results section establishes the evaluation methodology for tracking, plate reading, and owner email dispatch alongside implemented fine schedules and observed exception queue distributions.

I. INTRODUCTION

Unauthorized parking in restricted urban zones remains a major challenge for municipal traffic management. Vehicles parked in prohibited curbside areas obstruct emergency access, slow traffic flow, and require continuous manual patrolling. Relying on manual observation and paper-based ticketing is time-consuming, prone to inconsistent enforcement, and slow to recover fines [1], [3], [4].

Several operational challenges motivate this work: (i) continuous monitoring of restricted no-parking boundaries and tracking of vehicle dwell duration [1], [3]; (ii) rapid license plate extraction and owner database lookup [2], [6]; (iii) handling missing, blurry, or low-light plates that automated Optical Character Recognition (OCR) cannot verify alone [2], [5]; and (iv) integrating warning notifications, officer exception review, e-Challan generation, and online payment settlement in a single workflow [4].

PARK-ALERT addresses these challenges through a web-based system built with an HTML/CSS/JavaScript frontend, a Python Flask backend, and an SQLite database. The main contributions of this work are:

- **Spatial ROI geofencing and dwell tracking:** an officer defines a four-point ROI polygon on surveillance footage; YOLOv8 [8] with ByteTrack [7] tracks Car, Scooter/Bike, Bus and Truck classes and measures stationary dwell in seconds [3].
- **Tiered grace-period escalation and ANPR:** background multi-pass EasyOCR [9] with Indian plate normalization sends a warning at 20 seconds; vehicles still parked at 30 seconds are escalated to time-based fines [2], [6].
- **Officer exception queue and audit trail:** missing, blurry or unreadable plates go to a categorized queue with audible alerts, manual plate entry, remarks and an audit log [2], [5].
- **e-Challan dashboards and online settlement:** Unpaid and Paid dashboards, printable e-Challans, reminder and receipt emails, and Razorpay test-mode settlement [4].

Section II reviews related work, Section III describes the methodology, Section IV presents the evaluation and discussion, and Section V concludes the paper.

II. LITERATURE SURVEY

Automated parking enforcement has been explored with computer vision, deep learning, image enhancement and digital penalty workflows [1]–[6]. Silva, Alves and Ferreira [1] applied deep learning to parking surveillance, but with limited duration tracking and penalty escalation. Chen, Wang and Zhang [3] improved illegal-parking identification in complex urban scenes but left duration alerts and penalties unaddressed. Kumar and Gupta [2] studied real-time ALPR for smart-

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city traffic, which is sensitive to lighting and viewing angle. The ICTVSS model [5] improved plate recall with image enhancement but did not address duration-based penalties. The deep-learning ALPR framework [6] achieved high detection accuracy with CNNs and EasyOCR but lacked a complete enforcement workflow. Patel and Shah [4] linked IoT violation monitoring to automated fine generation without vision, ANPR or photographic evidence handling. Table I summarises this comparison. It is qualitative, because the works were not re-run on a shared dataset.

TABLE I QUALITATIVE COMPARISON WITH RELATED WORK

Work	ROI dwell tracking	ANPR / OCR	Penalty and enforcement workflow
Silva et al. [1]	Partial	Not stated	Partial (limited escalation)
Kumar and Gupta [2]	Not stated	Yes	Not stated
Chen et al. [3]	ROI detection only	Not stated	Not addressed
ICTVSS [5]	Not stated	Enhancement for recall	Not addressed
Deep ALPR [6]	Not stated	Yes (EasyOCR)	No complete workflow
Patel and Shah[4]	Not stated	Not stated	Yes (fine generation)
PARK-ALERT	**Yes (4-point ROI)**	**Yes (multipass)**	**Yes (grace, challan, payment)**

III. PROPOSED METHODOLOGY

A. System Architecture

PARK-ALERT uses a client-server architecture that separates the browser frontend, the Flask backend, background worker threads and the SQLite database, as shown in Fig. 1. The frontend provides operator and public interfaces and communicates with the backend over HTTP/JSON. The backend handles authentication and sector binding, vehicle registration, MJPEG live streaming, background ANPR and email tasks, violation and alert endpoints, and payments. SQLite stores officers, registered vehicles, violations, officer alerts, audit logs and evidence references.

TABLE II TECHNOLOGIES USED AND THEIR PURPOSES

Technology	Purpose
HTML, CSS, JavaScript	Surveillance HUD, video upload, Unpaid/Paid dashboards, Unreadable Plate Alerts console, e-Challan views
Python with Flask	RESTful routes, session and sector handling, MJPEG streaming, background dispatch, payment endpoints
OpenCV, YOLOv8, ByteTrack	Frame capture, vehicle detection, ROI polygon containment, multi-object dwell tracking
EasyOCR and plate lookup	Multi-pass plate text extraction, Indian plate normalization, registered-vehicle matching
SQLite	Officers, vehicles, violations, officer alerts, incident audit logs, payment references
Email service and Razorpay	Warning, penalty, reminder, receipt and officer alert emails; Razorpay test mode and simulation

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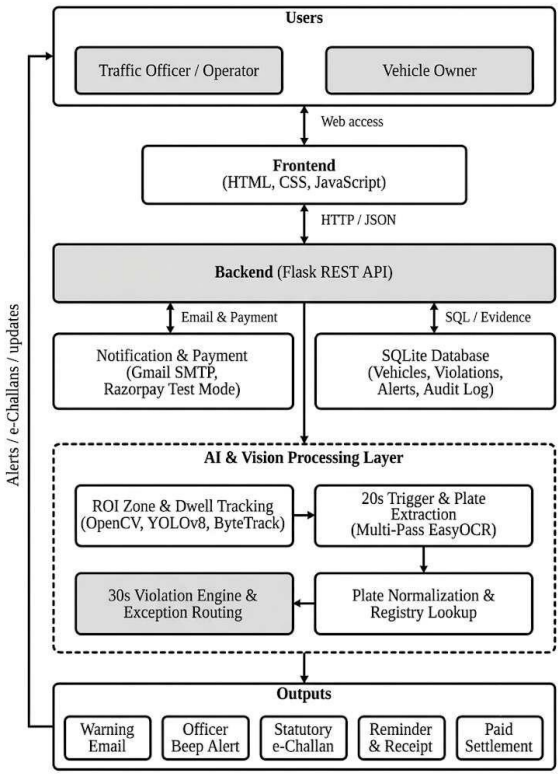


Fig. 1 System architecture of PARK-ALERT.

B. Officer Authentication and Sector Binding

Traffic officers sign in with a PIN and are bound to one enforcement sector, which the session keeps across requests. Vehicle owners do not log in; they reach challan and payment pages through links in their notices. Officers upload footage, define the ROI, view live violations with an audible-alert toggle, and move between the Unpaid, Paid and Unreadable Plate Alerts views.

C. ROI Dwell Tracking and Multi-Pass ANPR

Frames are read at native resolution and vehicles are tracked inside the configured ROI with YOLOv8 [8] and ByteTrack [7]. Stationary dwell is measured in seconds, keyed by track and start frame. At the 20-second trigger, a background worker runs multi-pass EasyOCR [9] with Indian plate normalization. Candidates are matched against registered vehicles in SQLite. Matched vehicles receive a warning email; unmatched or unreadable plates are routed to exception handling.

D. Grace-Period Escalation

Vehicles still stationary at 30 seconds are recorded as violations. The fine is Rs. 500 at 30 seconds plus Rs. 200 for each additional 10-second block, computed by a single fine function in the backend. Each violation stores the vehicle, plate, dwell duration, fine, timestamp, status and evidence path, and duplicate records for the same tracked vehicle in a session are prevented.

E. Challan Management and Settlement

Confirmed violations appear on the Unpaid and Paid dashboards and in printable e-Challans. Officers can send reminder emails to registered owners. Settlement uses Razorpay test-mode verification or a simulated payment mode (PAYMENT_SIMULATION), which marks the record PAID with a payment reference; receipt emails can then be sent from the Paid dashboard.

F. End-to-End Operational Workflow

The officer logs in, uploads footage and defines the ROI. Vehicles inside the ROI are tracked; at 20 seconds, background ANPR runs and a registered match triggers a warning, while an unresolved plate creates an officer alert. Vehicles still parked at 30 seconds are logged as violations, settled, and closed with reminder and receipt emails, as shown in Fig. 2.

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G. Exception Routing and Verification Decisions

Each unresolved incident is assigned to one of three categories from its crop diagnostics and OCR text. Table III defines the routing rules, and Table IV summarises the verification decisions available to the reviewing officer.

TABLE III EXCEPTION CATEGORIES AND ROUTING RULES

Category	Routing rule
No Plate Number	No plate text was read and the crop shows no motion blur, glare or low-light degradation.
Blurry Plate Number	Motion blur, extreme viewing angle, low-light or glare diagnostic, partial text (fewer than 4 characters), or a low-confidence registry match.
Unreadable	Four or more characters were extracted from a sharp crop but do not match any registered vehicle.

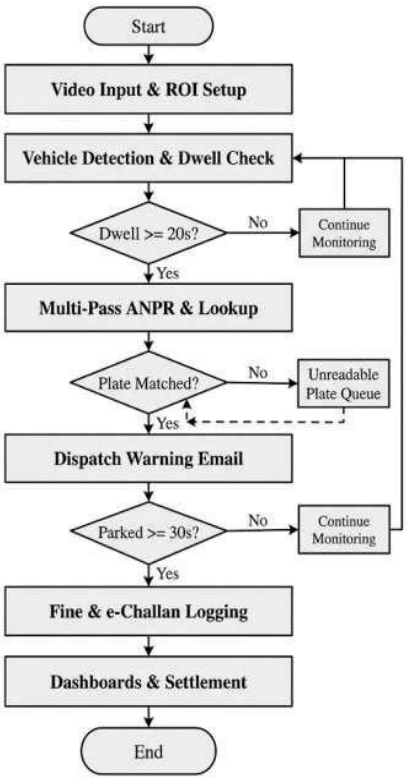


Fig. 2 End-to-end detection, verification, and e-Challan workflow of PARK-ALERT.

TABLE IV VERIFICATION DECISIONS AVAILABLE TO THE OFFICER

Category	Available verification decisions
No Plate Number	Missing plate confirmed; plate covered or obstructed; plate visible in another frame; correct plate number identified; camera or image quality issue; requires further investigation
Blurry Plate Number / Unreadable	Correct plate number identified (manual entry, owner lookup, notice dispatch); still unreadable after verification; cannot read from image, move to Unreadable (Blurry only); requires further investigation

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H. Evidence Handling and Multi-Pass Plate Reading

Two evidence images are saved from the native-resolution frame for every episode that reaches the alert or violation stage: a full vehicle snapshot showing spatial context inside the ROI, and a focused plate crop, padded and upscaled to at least 360 pixels wide. For two-wheelers the crop search covers the full width of the lower part of the vehicle box, where plates usually sit.

Single-pass OCR struggles with varied lighting, dark or green electric-vehicle plates, and stacked two-row Indian plates. The plate reader therefore applies several passes: native BGR inference, CLAHE with bilateral filtering, HSV dark/green background isolation, inverted Otsu thresholding, and adaptive morphological closing. Plate-shaped regions are read separately using dark and bright grey-level thresholds. Detections are deduplicated, clustered into rows by vertical centre, ordered left to right, and normalized to the state-district-series-number structure with confusion-pair and transposition checks before database verification. A plate is accepted only when exactly one registered vehicle matches.

TABLE V SYSTEM CONFIGURATION PARAMETERS

Parameter	Configured value
Warning email trigger (dwell duration)	20 seconds
Violation recording threshold	30 seconds
Time-based fine schedule	Rs. 500 base fine + Rs. 200 per additional 10-second block
Vehicle classes tracked	Car, Scooter/Bike, Bus, Truck
Detector input size	1280 px (configurable)
Detection confidence / NMS IoU	0.25 / 0.70
ByteTrack high / low / new-track thresholds	0.25 / 0.10 / 0.28
ByteTrack track buffer	180 frames
Background ANPR worker pool	5 concurrent threads

ALGORITHM 1.
PER-VEHICLE DWELL, ANPR AND DISPATCH FLOW

Execution Steps	
1:	Detect vehicles inside frames and assign persistent track IDs using ByteTrack.
2:	Test lower-box probe points (centre, bottom edge, and 25% and 75% of width) against the four-point ROI polygon; start or update the stationary dwell timer.
3:	At 20 seconds, extract a native-resolution vehicle crop and run multi-pass EasyOCR in a background worker.
4:	Normalize candidate strings and query the registered vehicles table in SQLite.
5:	If matched, dispatch one warning e-mail per plate per session and merge duplicate tracks of the same plate.
6:	If unmatched, raise an officer alert with its diagnostic classification, unless an alert already exists at that spot.
7:	At 30 seconds or beyond, log matched vehicles as violations with calculated fines; record unmatched vehicles only after manual officer plate verification.

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I. Notifications and Payment Settlement

The platform sends five types of e-mail: a warning at 20 seconds to the registered owner, a statutory penalty notice at the 30-second violation, an officer alert when a plate is not verified, a payment reminder for unpaid challans, and a receipt after settlement (Table VI). Penalty notices carry the e-Challan details and the fine. Email and payment work runs off the video thread, so a slow SMTP server or payment call does not stall live surveillance. Officer alerts are written to the database when raised, so the Unreadable Plate Alerts queue is complete after a page reload or a restart.

TABLE VI NOTIFICATION TYPES, TRIGGERS AND RECIPIENTS

Notification	Trigger	Recipient
Warning e-mail	Registered plate matched at 20 s	Registered owner
Penalty / e-Challan notice	Vehicle still parked at 30 s	Registered owner
Officer alert	Plate not verified at 20 s	Officer queue (on-screen, with beep)
Payment reminder	Officer action on Unpaid dashboard	Registered owner
Receipt	Settlement recorded	Registered owner

J. Access Control and Audit Trail

Officers sign in with a PIN and are bound to one enforcement sector. The session carries the sector, so alerts, violations and challans shown to an officer are limited to that sector. Vehicle owners do not log in. Each officer action on an alert, including the decision, remarks, the plate entered and the notice status, is written to an append-only incident audit log, so every change to an incident can be traced to the officer who made it.

K. Design Decisions

Table VIII records the main design decisions and the reason for each. The decisions keep automated actions limited to verified plates and leave every other case to a person.

TABLE VIII DESIGN DECISIONS AND THEIR RATIONALE

Decision	Rationale
Warning at 20 s; violation at 30 s	A warning gives the owner time to move before a fine is recorded.
No violation without a verified plate	A violation row must name a registered owner; garbage readings would otherwise reach challans.
Separate vehicle and plate images	The officer needs both the vehicle context and a readable plate.
ANPR and e-mail off the video thread	Slow OCR or SMTP calls must not stall the live feed.
Officer verifies unreadable plates	Automated reading is not reliable in all conditions; a person makes the final call.
Single SQLite database	Suited to one site and one operator team; the schema can move to a server database if deployment grows.

IV. RESULTS AND DISCUSSION

The evaluation of PARK-ALERT examines three core operational pipelines—vehicle tracking inside the ROI, multi-pass OCR number-plate recognition, and warning email dispatch to the registered owner—alongside the implemented fine escalation rule and observed exception queue behavior.

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A. Evaluation Metrics and Measurement Protocol

To evaluate detection, tracking, OCR and dispatch reliability against manually annotated ground-truth video clips, the following standard metrics are defined:

$$\text{Precision} = TP / (TP + FP), \quad \text{Recall} = TP / (TP + FN) \qquad (1)$$

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \qquad (2)$$

$$\text{Exact Plate Accuracy (\%)} = (N_{exact} / N_{plates}) \times 100 \qquad (3)$$

$$\text{Dispatch Accuracy (\%)} = (N_{correct_owner} / N_{matched}) \times 100 \qquad (4)$$

For each test clip, an annotator records vehicle presence inside the ROI (IoU ≥ 0.5), ground-truth stationary dwell intervals and the actual registration numbers. Tracking consistency is evaluated via identity switches and dwell-time error $|t - t|$. Plate reading is measured calc actual by exact normalized match rate, OCR processing latency per background job and exception-queue routing rate. Owner dispatch accuracy verifies that automated warning emails reach the exact address mapped to the true owner in the registry.

TABLE VII EVALUATION FRAMEWORK ACROSS PIPELINE STAGES

Pipeline stage	Evaluation metrics	Current evaluation status
ROI vehicle detection and tracking	Precision, recall, F1-score, ID switches, dwell-time error (s)	Protocol and metrics defined; requires annotated video ground-truth logs
Multi-pass OCR plate reading	Exact plate match (%), character accuracy (%), OCR latency (s)	Multi-pass pipeline verified; requires labelled plate benchmark runs
Owner lookup and email dispatch	Correct owner email match (%), SMTP delivery rate (%), dispatch latency (s)	SMTPS retry and registry matching verified; requires full trial logs
Grace-period fine escalation	Deterministic fine amount (INR) vs. stationary dwell duration (s)	Verified directly from implemented schedule (Fig. 3)
Exception queue categorization	Incident distribution across No Plate, Blurry Plate and Unreadable	Observed on deployed interface snapshot (N = 20, Fig. 4)

B. Implemented Time-Based Fine Escalation

Figure 3 illustrates the deterministic fine escalation schedule enforced by the backend. At 20 seconds of stationary dwell inside the ROI, background ANPR runs and a preventive warning is dispatched to the registered owner before any monetary penalty is assessed. If the vehicle remains parked at the 30-second violation threshold, a base fine of Rs. 500 is recorded, increasing by Rs. 200 for every additional 10-second block.

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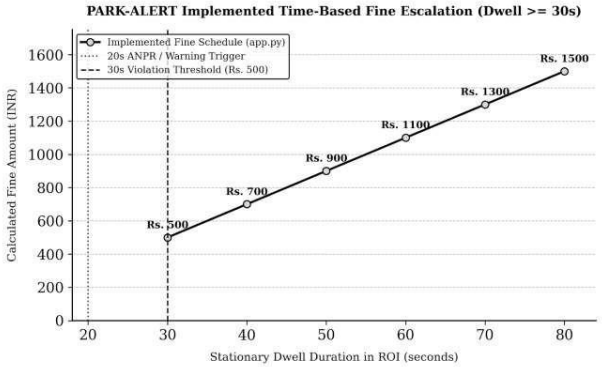


Fig. 3 Implemented time-based fine escalation schedule (Rs. 500 base at 30 s, +Rs. 200 per 10 s).

C. Observed Exception Queue Distribution

Figure 4 presents the distribution of unresolved incidents recorded in the Unreadable Plate Alerts console during system testing (N = 20 total incidents). Of the 20 routed incidents, 10 (50.0%) were categorized as No Plate Number, 3 (15.0%) as Blurry Plate Number, and 7 (35.0%) as Unreadable. Routing these cases to the officer console with zoom and enhancement controls prevents unverified citations from being issued automatically while preserving a complete audit trail when an officer manually identifies a registered plate. This distribution describes one snapshot, not a measured rate.

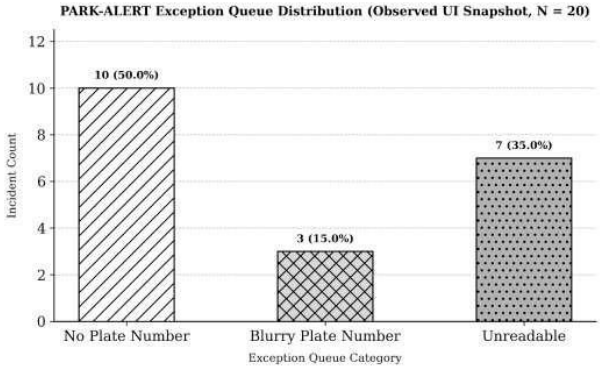


Fig. 4 Exception queue incident distribution across categories (observed interface snapshot, N = 20).

D. Discussion and Limitations

Decoupling live MJPEG streaming from background OCR and e-mail threads keeps the operator HUD responsive while multi-pass plate extraction and SMTP delivery run. Separating automated notices for verified registry matches from human-in-the-loop review of missing or blurry plates ensures accountability in enforcement.

Practical limitations remain: (i) OCR accuracy is sensitive to extreme camera angles, motion blur, glare and obscured two-wheeler plates, necessitating manual officer review; (ii) automated owner warning and penalty emails depend on accurate plate-to-owner mappings in the vehicle registry; (iii) high-resolution inference (1280 px) runs slower than real time on CPU-only hardware, requiring configurable input scaling or GPU acceleration for multi-stream deployments; and (iv) full quantitative precision, recall, OCR latency and email delivery benchmarks require multi-clip ground-truth video trials across varied lighting and traffic densities.

E. Threats to Validity and Future Work

- **Ground truth:** dwell boundaries and plate text are judged by a human annotator and may differ between annotators.
- **Clip selection:** results hold for the clips and cameras tested; a different viewing angle, mounting height or traffic density may change the thresholds that work best.
- **Payments:** settlement was tested in Razorpay test mode and in simulation only; no live transactions were processed.

The next step is evaluation on annotated real-world video datasets, with footage from several cameras, mounting heights and traffic densities, so that the thresholds in Table V can be checked against more than one site.

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Further work will measure end-to-end latency from the 20-second trigger to the warning email on the deployed hardware, and will test whether a lower detector input size keeps plate recall acceptable while reducing processing time on CPU-only machines.

F. Processing Configuration

Processing speed is governed by three settings. The detector input size is read from the PARK_INFERENCE_SIZE environment variable and defaults to 1280 px, so it can be lowered for CPU-only runs. The live MJPEG stream is encoded at JPEG quality 85 with INTER_LINEAR resizing, which reduces the cost of serving frames to the operator dashboard. Background ANPR runs on a pool of five worker threads, so plate reading does not block frame processing. Plate reading and evidence images are still taken from the native-resolution frame. Lowering the input size trades processing time against the detection of small plates and distant two-wheelers, so the setting should be checked on the target footage before operational use.

These settings matter most in deployment, where a single operator may monitor several zones. Because every configured value is held in one place, a change to input size, worker count or stream quality does not require changes to the tracking or enforcement logic.

VI. CONCLUSION

This paper presented PARK-ALERT, a web-based automated no-parking surveillance and violation management system built with HTML, CSS and JavaScript dashboards, a Python Flask backend and an SQLite database. It integrates four-point ROI geofencing, pre-trained YOLOv8 detection with ByteTrack tracking, background multi-pass EasyOCR with Indian plate normalization, tiered grace-period escalation with time-based fines, an officer exception queue with audible alerts and audit logging, and Unpaid and Paid challan dashboards with reminder, receipt and payment settlement workflows. PARK-ALERT supports traffic enforcement personnel while keeping human verification for unreadable or missing plates, and future work will evaluate detection, tracking, OCR and latency on annotated real-world video datasets.

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