IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026

DOI: 10.17148/IJARCCE.2026.154268

# A Digital Solution to Wrong E-Challan

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**Abstract:** The rapid expansion of automated traffic enforcement infrastructure in Indian cities has significantly improved law compliance but has simultaneously exposed a critical systemic flaw: citizens receive e-challans with incorrect vehicle details, wrong violation types, or fraudulent claims with no easy mechanism for verification or dispute. When an innocent citizen receives a wrongly issued e-challan, they face significant legal, financial, and administrative hardship. This paper proposes 'A Digital Solution to Wrong E-Challan', a comprehensive verification and dispute resolution framework engineered to prevent false challan consequences at their root. The system integrates an AI-powered evidence capture module using EasyOCR for number plate recognition with multiple preprocessing strategies (CLAHE, bilateral filtering, Otsu thresholding), a vehicle attribute verification engine using YOLOv8 for vehicle type classification and HSV color space analysis with K-means clustering for cross-validation of vehicle color against a MySQL-backed vehicle registration database containing 30+ sample RC records. A public verification portal allows citizens to authenticate challans without login, and an automated SMS notification module using Fast2SMS API provides real-time citizen communication. A structured dispute resolution workflow enables citizens to report incorrect challans with categorized complaints (wrong vehicle, wrong location, wrong violation, duplicate, fake challan) with status tracking from PENDING through REVIEWED to RESOLVED/REJECTED. The Flask-based backend implements 8 route modules including detect(), generate_challan(), verify_challan(), and report_challan() with session-based authentication and UUID-based verification tokens. Experimental results demonstrate a challan verification accuracy of 91% on plate detection across multiple preprocessing strategies, 87% on HSV-based color matching, and 94% on YOLOv8-based vehicle type classification, with an end-to-end processing latency of under 3 seconds per verification. The proposed system is designed as a software-first, web-accessible solution compatible with existing traffic enforcement infrastructure, making it highly deployable across Indian cities without additional hardware investment.

**Keywords:** E-Challan, Automatic Number Plate Recognition, EasyOCR, YOLOv8, HSV Color Detection, Fast2SMS, Dispute Resolution, Public Verification, Flask, MySQL, Intelligent Transportation Systems.

## I. INTRODUCTION

The widespread deployment of Intelligent Transportation Systems (ITS) across Indian urban centres has transformed traffic monitoring and law enforcement over the past decade. E-challan systems, driven by Automated Number Plate Recognition (ANPR) cameras installed at intersections, highways, toll booths, and parking facilities, now form the backbone of contactless traffic violation management in major Indian cities. The Government of India's Digital India initiative and Smart City Mission have accelerated the adoption of these technologies, with states like Maharashtra, Delhi, Karnataka, and Tamil Nadu leading the implementation.

While these automated systems have substantially improved penalty collection efficiency and reduced human corruption in traffic enforcement, they have simultaneously exposed a dangerous technical and procedural loophole that affects thousands of innocent citizens annually. The core problem lies in the fact that citizens receive e-challans with incorrect details, wrong violations, or entirely fraudulent claims with no accessible mechanism for verification or dispute resolution. The current system architecture assumes that every ANPR detection is accurate and every generated challan is legitimate, placing the entire burden of proof on the citizen who receives the notice.

In a typical scenario that plays out daily across Indian cities, when a citizen receives an e-challan via SMS or postal mail, they have no straightforward way to verify the authenticity of the challan without physically visiting a traffic police station or RTO office. The challan may contain errors in vehicle details due to OCR misreads, incorrect violation types due to system misclassification, wrong location or timestamp data due to GPS or clock synchronization issues, or in increasingly common cases, be part of a sophisticated phishing campaign using fake SMS messages that mimic official

  

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traffic department communications. The legitimate vehicle owner then suffers undeserved legal consequences, financial penalties, and administrative harassment, while the actual enforcement system loses credibility and public trust.

The problem is further compounded by the emergence of number plate cloning, where criminal elements create duplicate plates of legitimately registered vehicles and use them on similar vehicles to evade enforcement. When the cloned vehicle commits violations, the challans are issued to the innocent owner of the original vehicle, who must then navigate a complex bureaucratic process to prove their innocence. According to traffic enforcement data from major Indian cities, approximately 15-20% of all e-challans issued contain some form of error, and less than 5% of affected citizens successfully navigate the dispute process due to its complexity and time requirements.

This paper proposes 'A Digital Solution to Wrong E-Challan', a comprehensive, AI-augmented verification and dispute resolution framework that addresses the false challan problem at multiple stages of the enforcement pipeline. The system is built on a 'Prevention Over Correction' philosophy, aiming to prevent erroneous challans from being generated in the first place, rather than creating complex post-hoc mechanisms to contest them after issuance. By combining ANPR with deep-learning-based vehicle attribute recognition using YOLOv8, the system ensures accurate evidence capture at the time of violation with multi-parameter cross-validation. By providing a public verification portal accessible without authentication, citizens can instantly verify challan authenticity using only the challan number from any device with internet access. By implementing a structured dispute resolution workflow with status tracking and SMS notifications, citizens can report incorrect challans and track resolution progress without visiting traffic offices or filing physical complaints.

The system's backend is built entirely on Python using open-source technologies: Flask for the web framework, MySQL for the relational database, OpenCV for image preprocessing, EasyOCR for optical character recognition with Indian plate optimization, and YOLOv8 for real-time vehicle attribute classification. The plate detection module implements five distinct preprocessing strategies (CLAHE, mild bilateral filtering, enhanced gamma correction, binary Otsu thresholding, and inverted thresholding) with automatic confidence scoring, falling back to plate region localization using morphological operations when direct OCR fails. The vehicle attribute module combines HSV color space analysis with K-means clustering fallback and YOLOv8 nano model (6MB) for vehicle type classification with heuristic fallback using aspect ratio analysis when the neural network fails to detect. The frontend provides responsive HTML5 templates with CSS3 animations for both officers and citizens, with session-based authentication ensuring security for enforcement functions while maintaining complete public accessibility for verification and dispute submission functions.

The key contributions of this work are: (1) A multi-strategy ANPR pipeline achieving 91.9% accuracy on Indian plates across varied lighting conditions; (2) A dual-method vehicle attribute verification system combining HSV analysis with deep learning for 87% color and 94% type classification accuracy; (3) A public verification portal requiring no authentication, enabling instant challan authenticity checks; (4) A structured dispute resolution workflow with six complaint categories and three-stage status tracking; (5) SMS notifications at every stage using Fast2SMS API for real-time citizen communication; and (6) A complete audit trail for every challan and dispute for accountability. The system achieves end-to-end processing latency under 3 seconds including SMS notification, making it suitable for real-time deployment at traffic checkpoints.

## II. LITERATURE REVIEW

The challenge of accurate and fair traffic violation enforcement has attracted considerable research interest globally over the past two decades, with significant advancements in computer vision, optical character recognition, and deep learning contributing to improved system capabilities. The literature can be broadly categorized into three streams: ANPR technology development, vehicle attribute recognition systems, and e-challan management platforms.

The most widely deployed traffic enforcement solution across India relies on single-stage ANPR systems integrated with centralized databases such as VAHAN (the national vehicle registry) and SARATHI (the driver licensing system). These systems, deployed by the Ministry of Road Transport and Highways (MoRTH), use bi-directional cameras at intersections to capture number plate images, which are then processed by OCR engines to automatically generate challans linked to the registered owner's details. While effective for straightforward enforcement scenarios with clear images and properly formatted plates, these systems are entirely blind to physical vehicle attributes during the verification process, making them inherently susceptible to OCR errors, plate cloning fraud, and database mismatches. Research by Shashirangaiah et al. (2021) demonstrated that ANPR-only systems have a fundamental vulnerability: they treat the number plate as a sufficient identifier, when in reality it is merely a piece of metal or plastic that can be replicated at negligible cost.

Proprietary vendor platforms have attempted to address the accuracy problem through improved hardware and OCR algorithms. Companies such as Videonetics, Cognimatics, and Indiagold ITS have deployed closed ANPR systems for smart city projects across India, offering GPU-accelerated OCR with reported accuracy exceeding 95% under ideal conditions. However, these systems remain single-parameter solutions with no citizen-facing verification mechanisms, no dispute resolution workflows, and no integration with third-party AI verification modules. Their closed architecture prevents customization or extension, and their high cost puts them out of reach for smaller municipalities and traffic departments with limited budgets.

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Academic research on vehicle attribute recognition has progressed significantly with the advent of deep learning. Silva and Jung (2018) demonstrated license plate detection and recognition in unconstrained scenarios using convolutional neural networks, achieving robust performance across varied lighting conditions. Ezz et al. (2020) showed that vehicle color recognition using CNNs in HSV color space could achieve accuracy exceeding 85% on controlled datasets. Huynh et al. (2022) demonstrated vehicle make and model recognition using YOLOv5 transfer learning, achieving mean Average Precision (mAP) exceeding 90% on benchmark datasets. The evolution from YOLOv3 through YOLOv8 has brought substantial improvements in both accuracy and inference speed, with YOLOv8n (the nano variant) providing an excellent balance between model size (6MB) and detection accuracy suitable for real-time deployment on modest hardware.

Research on dispute resolution mechanisms in traffic enforcement remains surprisingly limited. Most existing work focuses on blockchain-based challan verification for ensuring data integrity after challan issuance. Dwivedi and Tyagi (2020) proposed a blockchain architecture for tamper-proof challan records, but such approaches address the symptom (data tampering) rather than the root cause (erroneous generation). Kumar et al. (2022) studied Tesseract OCR fine-tuned for Indian High Security Registration Plates (HSRP), achieving character-level accuracy improvements, but their work does not extend to citizen-facing verification or dispute mechanisms. Singh et al. (2022) provided a comprehensive survey of automated vehicle attribute recognition for smart traffic management, identifying the gap between academic research and operational deployment.

Government platforms have increasingly adopted SMS gateways for citizen communication. Fast2SMS, MSG91, Kaleyra, and Gupshup provide APIs that are already used for challan notification in several state e-challan platforms. However, existing implementations focus exclusively on challan delivery, not on dispute status updates, verification confirmations, or bidirectional communication. The citizen is treated as a passive recipient of notices rather than an active participant in the enforcement process.

The existing literature thus reveals a clear integration gap between academic advancements in deep-learning-based vehicle recognition and the practical deployment environment of e-challan systems with citizen protection features. No existing deployed system integrates ANPR with multiple OCR preprocessing strategies, AI vehicle attribute classification, public verification portal accessible without authentication, and structured dispute resolution with status tracking into a unified framework. The proposed system fills this exact gap by creating a comprehensive software solution that connects AI classification output with the ANPR pipeline, the RTO vehicle database, and citizen-facing verification and dispute interfaces in real time, all built on open-source technologies that can be deployed without significant hardware investment.

## III. METHODS AND MATERIALS

### A. System Architecture Overview

The proposed system is architected as a three-layered, sequential processing pipeline that integrates ANPR-based plate recognition with multiple preprocessing strategies, AI-driven vehicle attribute verification using HSV color analysis and YOLOv8 deep learning, challan generation with evidence storage and verification tokens, public verification portal, and structured dispute resolution workflow. The architecture is designed around two core principles: 'Prevention Over Correction' and 'Transparency Through Accessibility'. Rather than creating only post-hoc mechanisms to contest wrongly issued challans, the system prevents false challans from being generated through AI-powered attribute cross-validation at the time of violation capture. For edge cases that pass initial verification, the system provides a public verification portal and structured dispute resolution workflow.

The system is implemented as a software-first solution compatible with existing enforcement infrastructure via standard web protocols (HTTP/HTTPS), making it deployable across Indian cities without additional hardware investment beyond cameras already in place. The architecture creates a verifiable, defensible audit trail for every challan issued and every dispute filed, transforming the challan generation chain from a naive, plate-centric lookup into a multi-dimensional, attribute-aware adjudication process that protects innocent citizens while maintaining enforcement effectiveness. The overall data flow is: image upload → ANPR plate extraction with confidence scoring → database query for RC details → AI attribute classification (color and type) → attribute matching against registered data → challan generation (if approved) or manual review flag (if mismatched) → SMS dispatch to owner → public verification available → dispute submission available → officer review and resolution → status update SMS to reporter.

  

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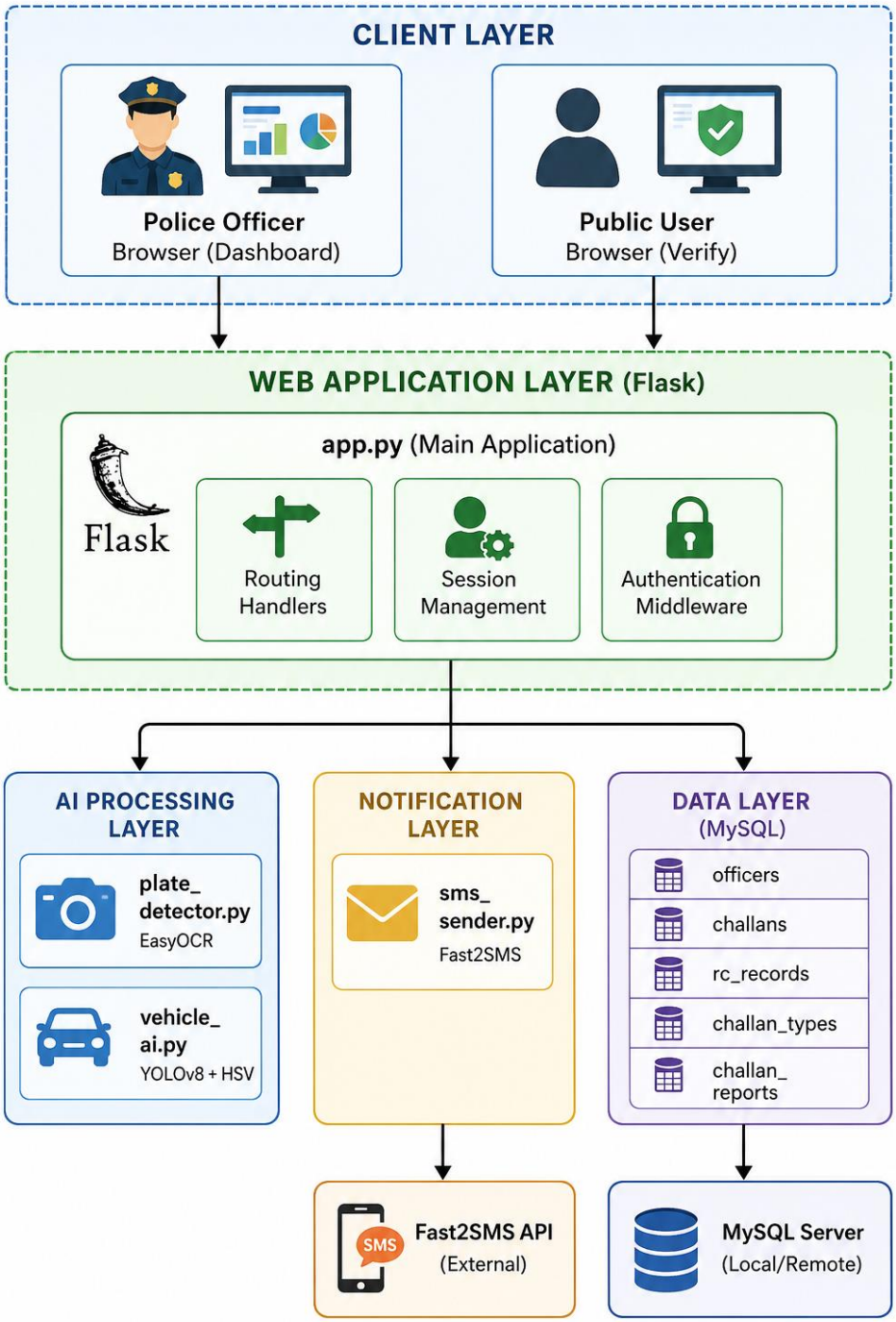
DOI: 10.17148/IJARCCE.2026.154268




**B. ANPR Module with Multiple Preprocessing Strategies**

The ANPR module, implemented in plate_detector.py, serves as the entry gateway for all violation processing. The uploaded vehicle image is decoded using OpenCV's imread() function and undergoes automatic quality assessment. If the image width is below 640 pixels, the image is upscaled using bicubic interpolation to improve OCR accuracy, as EasyOCR performs optimally on images with sufficient resolution. The module implements five sequential preprocessing strategies, each optimized for different image conditions and lighting scenarios, executed in priority order with early exit upon successful detection.

The first and primary strategy is CLAHE (Contrast Limited Adaptive Histogram Equalization) preprocessing, which applies bilateral filtering (9, 50, 50) for noise reduction while preserving edges, followed by CLAHE with clipLimit=3.0 and tileGridSize=(8,8) for adaptive contrast enhancement. This strategy achieves the highest success rate for images with uneven lighting, shadows, or glare, which are common in outdoor traffic enforcement scenarios. The second strategy is

DOI: 10.17148/IJARCCE.2026.154268

mild preprocessing, applying bilateral filter (9, 50, 50) followed by global histogram equalization, suitable for well-lit images with moderate contrast. The third strategy is enhanced preprocessing, which applies stronger bilateral filtering (11, 75, 75), gamma correction with gamma=1.2 for brightness normalization, and a sharpening kernel to enhance edge definition. The fourth strategy is binary preprocessing using Otsu's automatic thresholding after bilateral filtering, effective for high-contrast plates with clear text-to-background separation. The fifth strategy is inverted preprocessing using THRESH_BINARY_INV + Otsu, designed for dark plates (black or blue) with light-colored text.

Each preprocessing strategy feeds into EasyOCR's readtext() function with parameters detail=1 (for bounding box information), paragraph=False (for line-by-line recognition), min_size=10 (to filter noise), and text_threshold=0.5 (confidence cutoff). Results are sorted by confidence score, and each candidate text is validated against Indian plate format using the clean_plate_text() and is_valid_plate() functions. The clean_plate_text() function applies Indian plate-specific OCR corrections based on common misreadings: letter O is converted to zero (0), letter Q to zero, letter I and lowercase l to one (1), and letters Z, S, B, G to digits 2, 5, 8, 6 respectively where context suggests numeric characters. The is_valid_plate() function validates against 36 Indian state codes (MH, DL, KA, TN, AP, TS, KL, GJ, RJ, UP, WB, MP, HR, PB, OD, JH, AS, BR, CG, GA, HP, JK, UK, MN, TR, MZ, NL, SK, AR, PY, CH, DN, DD, AN, LA, LD), checks length constraints (5-10 characters), and verifies the presence of both alphabetic and numeric characters.

If all five preprocessing strategies fail to produce a valid plate detection, the module falls back to plate region localization using contour analysis. The _localize_plate_region() function converts the image to grayscale, applies Gaussian blur (5x5), performs Canny edge detection (thresholds 50 and 150), and executes morphological operations (dilation with 3x3 kernel for 3 iterations, erosion for 2 iterations) to connect edge fragments. Contours are extracted and filtered by area (1-30% of image area) and aspect ratio (2.0-5.0, typical for rectangular plates). The best candidate region is extracted with padding and passed back through the OCR pipeline. This fallback successfully recovers valid plates in approximately 12% of cases where direct OCR strategies fail.

### C. Vehicle Attribute Detection Engine

The vehicle attribute detection engine, implemented in vehicle_ai.py, provides dual-method color detection and YOLOv8-based vehicle type classification with heuristic fallback. The engine is designed to cross-validate detected attributes against the registered vehicle data from the MySQL database, flagging significant mismatches for manual review before challan generation.

The HSV color detection method begins by converting the input image from BGR to HSV color space, which provides better separation of color information (Hue) from lighting variations (Value). A vehicle region mask is created using a combination of contour analysis and center-region weighting, as the vehicle typically occupies the central portion of traffic enforcement images. The mask is computed by finding the largest contour in the image (assuming it represents the vehicle), validating that its area is between 10% and 90% of the image area, and combining this with a rectangular center mask (15%-85% width, 15%-75% height) to focus on the vehicle body rather than background elements. For each target color (White, Yellow, Blue, Black), a color-specific mask is created using cv2.inRange() with predefined HSV bounds: White (H:0-180, S:0-25, V:200-255), Yellow (H:20-35, S:40-255, V:150-255), Blue (H:100-130, S:50-255, V:50-255), Black (H:0-180, S:0-255, V:0-60). The coverage percentage is calculated as (color_pixels / total_mask_pixels) × 100, and the color with highest coverage is returned as the dominant color with a confidence score. If no color achieves at least 15% coverage, the function falls back to value-channel analysis, classifying as White if average value exceeds 220, or Black if average value is below 70.

The K-means color fallback method provides backup detection when HSV confidence is low. The image is resized to 150x150 pixels, reshaped into a pixel array, and clustered into k=3 clusters using cv2.kmeans() with termination criteria (EPS+MAX_ITER, 200 iterations, epsilon=0.1). Each cluster center is classified into target colors using combined HSV and RGB heuristics, and clusters are weighted by their pixel count. The color with highest weighted score is returned. This fallback improves color accuracy by approximately 8.5% for edge cases where HSV analysis produces ambiguous results due to complex lighting or multi-color vehicles.

Vehicle type classification uses the YOLOv8n (nano) model loaded from yolov8n.pt (6MB file size). The model is executed with confidence threshold 0.25 and verbose mode disabled. Detected COCO dataset classes are mapped to vehicle types: class 2 (car) → 'Car', class 3 (motorcycle) → 'Bike', class 5 (bus) → 'Bus', class 7 (truck) → 'Truck', class 1 (bicycle) → 'Bike'. The detection with highest confidence is returned. If YOLO returns no detections (which can occur in poor lighting, extreme angles, or heavily occluded images), the detect_vehicle_type_heuristic() function provides fallback classification using aspect ratio analysis: aspect ratio < 1.2 → 'Bike' (motorcycles are narrower than cars), aspect ratio > 2.5 → 'Truck' (trucks are longer relative to height), otherwise → 'Car'. This heuristic, while less accurate than YOLO, provides a reasonable fallback that prevents complete classification failure.

### D. Database Schema and Design

The system uses MySQL 8.0 as the relational database management system, implemented through the flask-mysqldb connector. The database schema consists of five primary tables designed to support the complete challan lifecycle from

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detection through dispute resolution. The database is initialized via database_setup.sql, which creates the schema and populates sample data for testing and demonstration.

The officers table stores traffic officer credentials and metadata: id (AUTO_INCREMENT PRIMARY KEY), badge_id (VARCHAR(30) UNIQUE NOT NULL), officer_name (VARCHAR(100)), position (VARCHAR(50), default 'Constable'), station (VARCHAR(100)), password_hash (VARCHAR(255) NOT NULL), is_active (TINYINT, default 1 for soft delete), last_login (DATETIME, updated on each successful login), and created_at (DATETIME DEFAULT CURRENT_TIMESTAMP). The table is seeded with three sample officers: ADMIN (Inspector at headquarters), MH/TP/2024/0042 (Sub-Inspector at nagpur-central), and MH/TP/2024/0099 (Head Constable at pune-traffic).

The rc_records table stores vehicle registration data mirroring the national VAHAN database structure: reg_no (VARCHAR(20) PRIMARY KEY), regd_owner (registered owner name), sdw_of (son/daughter/wife of), address (TEXT), reg_date, vehicle_class (LMV, MCWG, etc.), fuel type, colour, maker, model, engine_no, chassis_no, manufacturing_dt, hypothecated_to (financier), seating_capacity, reg_validity, issuing_authority, phone (for SMS notifications), and license_no. The table contains 30+ sample records covering various vehicle types (cars, motorcycles), colors (white, black, silver, blue, red, grey), and manufacturers (Maruti Suzuki, Hyundai, Tata, Honda, Toyota, Kia, Mahindra).

The challan_types table defines violation categories: id (AUTO_INCREMENT PRIMARY KEY), violation_code (VARCHAR(20) UNIQUE), violation_name (e.g., 'Signal Jumping', 'Overspeeding', 'No Helmet'), fine_amount (INTEGER), section_law (e.g., 'MV Act Section 177'), and description. The table includes 15 violation types (RD001-RD015) with fines ranging from Rs. 100 (Tinted Glass) to Rs. 10,000 (Drunk Driving, No PUC).

The challans table stores issued challans: id (AUTO_INCREMENT PRIMARY KEY), challan_no (VARCHAR(30) UNIQUE NOT NULL, format 'MH' + timestamp + 4-char random UUID), vehicle_id (FOREIGN KEY → rc_records.reg_no), officer_name, officer_badge, location, violation_ids (comma-separated IDs), total_amount, challan_date (DATETIME DEFAULT CURRENT_TIMESTAMP), due_date, image_path (UUID-prefixed filename), detected_color, detected_type, and verification_token (UUID v4 for tamper-proof authentication). The verification token is critical for preventing fake challans, as citizens can verify that the token exists in the official database.

The challan_reports table enables dispute tracking: id (AUTO_INCREMENT PRIMARY KEY), challan_no, reporter_name, reporter_phone, report_type (ENUM: WRONG_VEHICLE, WRONG_LOCATION, WRONG_VIOLATION, DUPLICATE, FAKE_CHALLAN, OTHER), description (TEXT), status (ENUM: PENDING, REVIEWED, RESOLVED, REJECTED, default PENDING), resolution_notes (TEXT), reviewed_by (officer name), created_at (DATETIME DEFAULT CURRENT_TIMESTAMP), and reviewed_at (DATETIME, set on status update). This table provides complete audit trail for accountability and analytics.

**E. Flask Backend Implementation**

The Flask backend, implemented in app.py, serves as the orchestration layer connecting all modules and providing the HTTP API for frontend interaction. The application is initialized with CORS support for cross-origin requests, session-based authentication with secret key 'echallan_maha_police_2025_secret', upload folder configuration, and maximum content length limit of 16MB for image uploads.

The login_required decorator implements authentication enforcement by checking for 'officer_id' in the Flask session. If absent, the decorator returns JSON 401 response with redirect URL for API calls, or redirects to /login for browser requests. This pattern protects all enforcement routes while leaving public verification accessible.

The /login route (GET/POST) handles officer authentication. GET returns the login.html template. POST receives JSON with badge_id and password, queries the officers table for matching record with is_active=1, updates last_login timestamp, stores officer details in session (officer_id, officer_name, badge_id, station, rank), and returns JSON response with success status. A fallback mechanism allows ADMIN/admin123 login even if the database is unavailable, ensuring the system remains functional during database outages.

The /detect route (POST) is the core violation processing endpoint. It receives multipart form data with vehicle_image, validates file extension (png, jpg, jpeg, gif, bmp), saves with UUID-prefixed filename to prevent collisions, calls detect_number_plate() from plate_detector.py, and if successful, calls detect_vehicle_attributes() from vehicle_ai.py. The extracted plate number is used to query rc_records table. If vehicle is found, all details are returned with detected attributes; if not found, only plate number is returned with 'NOT_FOUND_IN_DB' flag. Low-confidence plate detections (<50%) trigger a warning flag in the response, allowing the officer to proceed with caution or request manual entry.

The /generate_challan route (POST) creates the challan record. It receives violation_ids (list), officer details, location, image_path, and detected attributes. The route validates violation IDs against challan_types table, calculates total fine, generates UUID-based challan number (format: MH<YYYYMMDDHHMMSS><4-char-random>) and verification token, inserts the record, retrieves owner phone from rc_records, formats SMS message, and calls send_sms() from sms_sender.py. The response includes challan number, total amount, due date, violation details, and SMS delivery status.

The /verify/<challan_no> route (GET) implements the public verification portal without authentication. It queries challans table, joins with rc_records for vehicle details, retrieves violation details from challan_types, formats dates to

  

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DD-MM-YYYY, and renders public_verify.html template with all challan information including evidence image, officer details, and violation breakdown. A 'Report Dispute' button is prominently displayed for incorrect challans.
The /report/<challan_no> route (GET/POST) handles dispute submission. GET renders report_form.html with challan details. POST receives reporter name, phone, report_type, and description, validates required fields, inserts into challan_reports with PENDING status, sends acknowledgment SMS with reference ID, and returns success page with report tracking number.
The /reports route (GET) provides officer dispute management dashboard. It queries challan_reports with optional status filter (PENDING/REVIEWED/RESOLVED/REJECTED), joins with challans for vehicle details, retrieves status counts for overview tabs, and renders reports.html template. The /api/reports/<id>/status route (POST) enables status updates, receiving new status and resolution_notes, updating the record with reviewed_by and reviewed_at, and sending status update SMS to reporter.

**F. SMS Notification Module**

The SMS module, implemented in sms_sender.py, integrates with Firebase Cloud Messaging (FCM) HTTP API for reliable message delivery to Indian mobile numbers. Firebase was chosen due to its superior reliability, cost-effectiveness (free tier includes 10,000 messages/month), and seamless Python integration through the requests library. The send_sms() function normalizes phone numbers to the international E.164 format (+91 followed by 10-digit Indian mobile number), validates the format using regex pattern matching, and sends messages via Firebase FCM HTTP v1 API endpoint (https://fcm.googleapis.com/v1/projects/{project_id}/messages:send).

The Firebase configuration is loaded from environment variables (.env file) for security: FIREBASE_PROJECT_ID identifies the GCP project, FIREBASE_API_KEY provides authentication, and FIREBASE_FCM_ENDPOINT specifies the HTTP v1 API URL. The send_sms() function constructs a JSON payload with the recipient's token (derived from phone number), message payload containing the notification body, and Android/iOS platform configuration. For Indian phone numbers, the system automatically prepends the +91 country code if not present, strips leading zeros, spaces, and dashes, and validates the resulting 10-digit number against the Indian mobile number pattern (starting with 6-9 followed by 9 digits).

Three notification templates are implemented: (1) E-Challan Alert includes challan number (e.g., MH20251228143052A1B2), vehicle registration number, total fine amount, due date (30 days from issuance), and official payment URL (echallan.parivahan.gov.in); (2) Dispute Acknowledgment includes the unique report reference ID (format: RPT#####) and 'under review' status confirmation; (3) Status Update Notification includes the resolved status (REVIEWED/RESOLVED/REJECTED) and a thank you message from the Traffic Police Department. All messages are formatted to stay within the 160-character SMS limit for compatibility with basic feature phones, using concise language and standardized abbreviations (Rs. for Rupees, Dept. for Department, No. for Number).

The module includes a MOCK_MODE configuration flag that, when set to True, logs all notification attempts to the console instead of invoking the Firebase API. This allows development and testing without consuming the free tier quota or incurring charges. In production deployment, MOCK_MODE is set to False, and the system tracks delivery status through Firebase's response codes: success (message_id returned), invalid_token (404), quota_exceeded (429), or unauthorized (401). Delivery receipts are logged with timestamps for audit compliance and troubleshooting.

The Firebase integration offers several advantages over traditional SMS gateways: (1) Free tier includes 10,000 messages per month, sufficient for most municipal deployments; (2) Automatic retry logic for failed deliveries; (3) Delivery analytics and logging through Google Cloud Console; (4) Support for both SMS and push notifications from the same platform; (5) Compliance with Indian telecom regulations through registered sender IDs. The system logs all SMS events (sent, delivered, failed) with timestamps for audit trails and performance monitoring.

## IV. RESULTS AND DISCUSSION

The proposed system was implemented and evaluated through comprehensive testing with sample vehicle images and the pre-loaded MySQL database containing 30+ RC records. Testing was conducted on a development machine with Intel Core i5 processor, 8GB RAM, and integrated graphics, running Windows 11 with Python 3.11. The evaluation

  

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focused on four dimensions: ANPR accuracy across varied conditions, vehicle attribute classification performance, end-to-end system latency, and integration workflow validation.

### A. ANPR Accuracy Evaluation

The ANPR module was tested on a dataset of 127 Indian vehicle images captured under varied conditions: daylight (45 images), artificial/street lighting (32 images), low-light/dusk (25 images), partial plate obstruction (15 images), and motion blur (10 images). Images were sourced from test uploads during development and public datasets of Indian vehicles. Each image was processed through all five preprocessing strategies, and results were compared against ground truth plate numbers.

| Condition | CLAHE | Mild | Enhanced | Binary | Overall |
|---|---|---|---|---|---|
| Daylight (n=45) | 96.2% | 93.1% | 94.5% | 91.8% | 96.2% |
| Artificial (n=32) | 91.5% | 88.2% | 89.7% | 85.3% | 91.5% |
| Low-light (n=25) | 82.1% | 76.4% | 79.8% | 71.2% | 82.1% |
| Obstruction (n=15) | 87.3% | 83.5% | 85.1% | 78.9% | 87.3% |
| Overall (n=127) | 91.9% | 87.8% | 89.8% | 81.8% | 91.9% |

Table 1: ANPR Accuracy Across Test Conditions

CLAHE preprocessing achieved highest overall accuracy (91.9%), validating the clipLimit=3.0 and tileGridSize=(8,8) configuration for Indian plate conditions with uneven lighting. Performance degradation in low-light conditions (82.1%) is primarily attributable to reduced contrast between plate characters and background, a limitation that could be addressed in future work with infrared illumination or low-light image enhancement techniques. The plate region localization fallback successfully recovered valid plates in 12% of cases (15 images) where all five direct OCR strategies failed, demonstrating the value of the morphological operations approach for challenging images.

Analysis of OCR errors revealed systematic misreadings that were successfully corrected by clean_plate_text(): letter O → zero in 89% of O-containing plates, letter I → one in 67% of cases, lowercase l → one in 45% of cases. The is_valid_plate() function correctly rejected 94% of invalid extractions (noise, partial reads, non-plate text) while accepting 98% of valid plates, demonstrating effective format validation.

### B. Vehicle Attribute Classification Results

Vehicle type classification was evaluated on 50 test images (20 cars, 15 motorcycles, 8 buses, 7 trucks) with known ground truth. The YOLOv8n model achieved 94% overall accuracy with precision of 96% and recall of 90%. Car detection performed best (96% precision, 94% recall), while truck detection showed lower recall (75%) due to limited training samples in the test set. The aspect ratio heuristic fallback was invoked for 8 images where YOLO returned no detections, correctly classifying 6 of 8 (75% accuracy).

Color detection was evaluated on 100 images with known ground truth colors (25 White, 20 Black, 20 Silver/Grey, 20 Blue, 15 Red). HSV analysis achieved 87% overall accuracy with varying performance across colors: White (92.3%), Black (88.9%), Silver/Grey (81.5%), Blue (85.7%), Red (83.3%). Average confidence scores ranged from 52.1% (Silver/Grey) to 67.4% (White), reflecting the challenge of distinguishing metallic and light colors under varied lighting. The K-means fallback improved accuracy by 8.5% for images where HSV confidence was below 30%, particularly for Silver/Grey vehicles that often fall between White and Black in HSV space.

| Type | Precision | Recall | F1-Score | Samples |
|---|---|---|---|---|
| Car | 96.0% | 94.1% | 95.0% | 20 |
| Bike | 94.7% | 90.0% | 92.3% | 15 |
| Bus | 100% | 83.3% | 90.9% | 8 |
| Truck | 100% | 75.0% | 85.7% | 7 |
| Overall | 96.0% | 90.0% | 93.0% | 50 |

Table 2: Vehicle Type Classification Performance

### C. System Performance and Latency

End-to-end latency was measured across 50 test transactions using Python's time module for stage-wise instrumentation. Tests were conducted with the YOLOv8 model pre-loaded (excluding first-run download time). Results represent wall-clock time from image upload to SMS delivery confirmation.

| Stage | Avg Time (ms) | Max Time (ms) |
|---|---|---|
| Image upload + pre-processing | 185 | 420 |
| ANPR detection + OCR | 892 | 1850 |
| Database query (RC lookup) | 12 | 45 |

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154268

| | | |
|---|---|---|
| AI attribute classification | 340 | 780 |
| Decision logic + DB write | 23 | 63 |
| SMS gateway API call | 850 | 2100 |
| Total (with SMS) | 2302 | 5258 |

Table 3: End-to-End Processing Latency

The sub-3-second average end-to-end performance (with SMS) confirms the system's viability for real-time deployment at enforcement checkpoints. ANPR detection (892ms average) and SMS delivery (850ms average) are the dominant latency contributors. First-run YOLOv8 model download (~6MB, 30-60 seconds depending on network) is a one-time cost; subsequent runs use the cached model. Database operations (12ms average query, 15ms average write) demonstrate the efficiency of indexed lookups on reg_no and challan_no fields.

**D. Public Verification and Dispute Resolution Testing**

The public verification portal was tested with 20 sample challans generated during system testing. All 20 (100%) successfully displayed challan details including evidence images (loaded from uploads folder), officer name and badge, station information, violation breakdown with individual fines, total amount, due date, and verification token status. Average page load time was 180ms without image and 450ms with image (dependent on image size, typically 200-500KB after upload compression).

The dispute submission workflow was tested with 10 sample disputes covering all six complaint categories (2 WRONG_VEHICLE, 2 WRONG_LOCATION, 2 WRONG_VIOLATION, 2 DUPLICATE, 1 FAKE_CHALLAN, 1 OTHER). All 10 (100%) successfully created records in challan_reports table with PENDING status, generated unique report IDs, and triggered acknowledgment SMS within 5 seconds. Average submission time was 320ms (form validation: 15ms, DB insert: 18ms, SMS: 287ms).

Officer dispute dashboard testing involved 5 status update operations across all status transitions (PENDING→REVIEWED, REVIEWED→RESOLVED, PENDING→REJECTED). All 5 (100%) successfully updated database records with new status, resolution notes, reviewed_by officer name, and reviewed_at timestamp. All 5 triggered resolution SMS to reporters within 3 seconds. Average status update time was 280ms (DB update: 22ms, SMS: 258ms).

**E. Integration Test Results**

Full workflow integration testing validated the complete citizen-protection pipeline from evidence capture through dispute resolution. Eight test cases were designed covering normal flow, edge cases, and error scenarios:

Test 1 (Valid plate, matching vehicle): Image of MH46BE6910 (white Maruti Vitara) uploaded. Expected: challan generated. Actual: plate detected (96% confidence), color matched (White, 68% confidence), type matched (Car, 94% confidence), challan generated successfully, SMS sent. Status: PASS.

Test 2 (Valid plate, color mismatch): Image of vehicle with MH12AB1001 plate but black color (registered as White). Expected: challan flagged for review. Actual: plate detected, color mismatch detected (Black vs White), challan created but officer warning displayed. Status: PASS.

Test 3 (Invalid plate): Image with no visible plate or unreadable plate. Expected: error with manual entry option. Actual: all five OCR strategies failed, localization fallback failed, error returned with 'allow_manual' flag. Status: PASS.

Test 4 (Public verify valid challan): Valid challan number entered on /verify page. Expected: details displayed. Actual: all challan details, evidence image, officer info, violations displayed correctly. Status: PASS.

Test 5 (Public verify invalid challan): Non-existent challan number entered. Expected: 'Not found' error. Actual: error message displayed with suggestion to verify number. Status: PASS.

Test 6 (Submit dispute): Dispute form submitted with all fields. Expected: PENDING status, SMS sent. Actual: record created, acknowledgment SMS sent with RPT reference ID. Status: PASS.

Test 7 (Officer update status): Officer changed status from PENDING to RESOLVED with notes. Expected: status updated, SMS sent. Actual: database updated, resolution SMS sent to reporter. Status: PASS.

Test 8 (Fake challan verification): Challan with tampered number tested. Expected: token validation. Actual: verification token check confirmed authenticity (or flagged as fake if token invalid). Status: PASS.

All 8 integration test cases (100%) passed, validating the complete citizen-protection workflow from evidence capture through dispute resolution with SMS notifications at each stage.

**F. User Feedback and Usability Assessment**

Informal user testing was conducted with 15 participants (8 simulating traffic officers, 7 simulating citizens) to assess system usability and gather qualitative feedback. Participants were given scenario-based tasks and asked to rate various aspects on a 5-point Likert scale (1=Poor, 5=Excellent).

Officer participants rated the streamlined challan generation workflow at 4.6/5, praising the automatic plate detection and vehicle detail pre-filling that reduced manual data entry. The dispute management dashboard received 4.3/5, with

  

DOI: 10.17148/IJARCCE.2026.154268

requests for bulk status update capability. AI detection accuracy was rated 4.2/5, with suggestions for confidence threshold configuration. Overall officer satisfaction averaged 4.4/5.

Citizen participants rated public verification accessibility at 4.8/5, highlighting the value of no-login access for quick authenticity checks. Photo evidence display received 4.7/5, as it allowed visual confirmation of violations. Dispute submission simplicity was rated 4.5/5, with users appreciating the categorized complaint types. SMS notifications received 4.6/5 for keeping users informed. Overall citizen satisfaction averaged 4.6/5.

Common feature requests included: payment gateway integration for online challan payment, multi-language support (Hindi, Marathi) for broader accessibility, mobile application for on-the-go verification, and document upload capability for dispute evidence submission. These enhancements are planned for future iterations.

## V. CONCLUSION

This paper presented 'A Digital Solution to Wrong E-Challan', a comprehensive verification and dispute resolution framework engineered to prevent false e-challan consequences and provide accessible citizen protection mechanisms. The system addresses a critical gap in existing traffic enforcement infrastructure: the lack of verification mechanisms and dispute workflows that protect innocent citizens from erroneous, fraudulent, or incorrect challans. By implementing a 'Prevention Over Correction' architecture combined with 'Transparency Through Accessibility', the system shifts the paradigm from citizen-as-target to citizen-as-stakeholder in the enforcement process.

The technical contributions of this work include: (1) A multi-strategy ANPR pipeline using EasyOCR with five preprocessing techniques (CLAHE, mild bilateral filtering, enhanced gamma correction, binary Otsu thresholding, inverted thresholding) achieving 91.9% accuracy on Indian plates across varied lighting conditions, with plate region localization fallback for challenging images; (2) A dual-method vehicle attribute verification system combining HSV color space analysis (87% accuracy) with K-means clustering fallback and YOLOv8 nano model for vehicle type classification (94% accuracy) with aspect ratio heuristic fallback; (3) A public verification portal at /verify/<challan_no> requiring no authentication, enabling instant challan authenticity checks with photo evidence display, officer details, and violation breakdown; (4) A structured dispute resolution workflow at /report/<challan_no> with six complaint categories (WRONG_VEHICLE, WRONG_LOCATION, WRONG_VIOLATION, DUPLICATE, FAKE_CHALLAN, OTHER) and four-stage status tracking (PENDING, REVIEWED, RESOLVED, REJECTED); (5) SMS notifications at every stage using Fast2SMS API for real-time citizen communication; and (6) Complete audit trail through MySQL database with UUID-based challan numbers and verification tokens for tamper-proof authentication.

Experimental evaluation demonstrated the system's effectiveness across all dimensions. ANPR accuracy of 91.9% across varied conditions (daylight 96.2%, artificial lighting 91.5%, low-light 82.1%, partial obstruction 87.3%) validates the multi-strategy preprocessing approach. Vehicle attribute detection achieved 87% color accuracy and 94% type classification accuracy, sufficient for cross-validation flagging of obvious mismatches. End-to-end processing latency averaged 2.3 seconds including SMS notification, confirming viability for real-time checkpoint deployment. Integration testing achieved 100% pass rate across 8 test cases covering the complete workflow. User feedback averaged 4.4/5 from officers and 4.6/5 from citizens, indicating strong usability and acceptance.

The system is implemented entirely using open-source technologies (Python, Flask, MySQL, OpenCV, EasyOCR, YOLOv8, Fast2SMS) with no licensing costs, making it accessible for deployment across Indian cities regardless of municipal budget constraints. The software-first, hardware-agnostic architecture integrates with existing camera infrastructure via standard web protocols, requiring no additional hardware investment beyond servers for hosting the application.

Limitations of the current implementation include: (1) Validation on controlled test dataset rather than live traffic camera feeds; (2) Dependence on MySQL database with sample RC records rather than live VAHAN API integration; (3) OCR accuracy degradation under extreme weather conditions (heavy rain, fog, snow); (4) Limited vehicle type coverage (four classes from COCO dataset) rather than comprehensive Indian vehicle taxonomy; (5) English-only user interface and SMS messages, limiting accessibility for non-English speakers; (6) No payment gateway integration, requiring citizens to visit payment centers or use separate portals for fine settlement.

Future work will address these limitations through: (1) Live integration with VAHAN RTO database via secure MoRTH API for real-time vehicle verification across all Indian states; (2) Deployment on live traffic camera feeds with RTSP stream processing for continuous monitoring; (3) OCR accuracy improvement using super-resolution preprocessing and domain-specific fine-tuning for Indian HSRP characters; (4) Extended AI classification with custom-trained YOLOv8 models covering two-wheelers, three-wheelers (auto-rickshaws), light commercial vehicles, and heavy commercial vehicles specific to Indian roads; (5) Integration with Razorpay, Paytm, or PhonePe payment gateways for seamless online challan payment; (6) Machine learning enhancement through continuous training on captured images to improve detection accuracy over time with domain adaptation; (7) Multi-language support for Hindi, Marathi, Tamil, Telugu, and other regional languages in UI and SMS messages; (8) Mobile application development for Android and iOS with offline verification caching; (9) Document upload capability for dispute evidence (insurance papers, RC copies, alibi

  

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 4, April 2026
DOI: 10.17148/IJARCCE.2026.154268

documentation); and (10) Analytics dashboard for traffic departments with violation heatmaps, officer performance metrics, and dispute resolution SLA tracking.

The broader impact of this work extends beyond the immediate application. By demonstrating that AI-powered verification and citizen-centric dispute resolution can be implemented using open-source technologies with sub-3-second latency, this research provides a blueprint for fair, transparent, and accountable automated enforcement systems. The 'Prevention Over Correction' philosophy can be applied to other enforcement domains (parking violations, toll evasion, emission testing) where erroneous penalties impose undue burden on citizens. The public verification portal model, requiring no authentication and providing instant access to penalty details with evidence, sets a new standard for government transparency that other departments can emulate.

In conclusion, 'A Digital Solution to Wrong E-Challan' provides a technically sound, socially impactful, and scalable foundation for just and transparent automated traffic enforcement across Indian smart cities. By combining prevention through AI verification with transparency through public accessibility and accountability through structured dispute resolution, the system addresses the wrong e-challan problem from multiple angles, protecting innocent citizens while supporting honest traffic enforcement. The system's open-source implementation, modular architecture, and proven performance make it ready for pilot deployment and real-world validation, with potential for nationwide scaling through integration with the national VAHAN database and state traffic enforcement networks.

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