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COMMUNITY-DRIVEN TRAFFIC LAW ENFORCEMENT WITH A REWARD MECHANISM

Fashil Rasool B*, Jaganath N*, Dhanakotti V*, Harshini P*
*Students, Department of Computer Science and Engineering
KGiSL Institute of Technology, Coimbatore, Tamil Nadu
Ms Suganthi A#
#Assistant Professor, Department of Computer Science and Engineering
KGiSL Institute of Technology, Coimbatore, Tamil Nadu
Sugantit@gmail.com

Abstract—India continues to face alarming road fatality rates due to non-compliance with traffic regulations. Despite the presence of CCTV surveillance and manual policing, the scale of violations outpaces enforcement capacity. The proposed work introduces a community-driven framework where citizens act as real- time contributors to traffic law enforcement through a mobile application. The application enables users to capture and submit photographic or video evidence of violations such as helmetless riding, triple-seating, and signal jumping. Each report is automatically tagged with GPS coordinates, date, and time before being uploaded to a secure cloud repository. Traffic au- thorities access a web- based dashboard to verify the reports and reward legitimate submissions through a point-based incentive mechanism redeemable as mobile recharges or digital coupons. The collected data feeds into an analytics engine that generates violation heatmaps and temporal statistics to identify high-risk zones. This work combines crowdsourcing, cloud computing, and artificial intelligence to deliver a sustainable, scalable, and cost-efficient solution. By turning citizens into active partners rather than passive observers, the system enhances account- ability, promotes behavioural change, and supports data-driven policy-making for safer roads across urban and semi-urban environments.

Index Terms—Crowdsourcing, Traffic Enforcement, Reward System, Cloud Computing, Artificial Intelligence, Road Safety, Smart City Governance

I. INTRODUCTION

Road safety is a multidimensional challenge that intertwines behavioural, infrastructural, and technological aspects of urban life. According to the World Health Organisation, developing countries account for over 90 per cent of global road fatalities, with two-wheeler riders forming a significant share. In India, despite stringent helmet laws, compliance remains inconsistent due to poor monitoring and limited enforcement resources. Existing mech- anisms rely on manual policing and fixedcamera surveil- lance, both of which are resource-intensive and geographi- cally constrained. The concept of citizen-centric governance in smart cities encourages participatory approaches where the public collaborates with authorities to ensure effective service delivery. This project adopts the same philosophy by empowering ordinary road users to become active enforcers through a simple technological interface. With the ubiquity of smartphones and affordable internet connectivity, crowd- sourcing evidence of traffic violations becomes both practical and scalable. The proposed system introduces an end-to-end ecosystem that merges mobile application development, cloud infrastructure, and data analytics. A user-friendly mobile app allows citizens to capture images or videos of violations; data is transmitted via secure APIs to a cloud database. Administrators review submissions through a dashboard that displays location, timestamp, and evidence. Once validated, the contributor earns reward points that can be redeemed digitally. Over time, the accumulated data builds a comprehen- sive violation database capable of revealing temporal patterns, accident-prone zones, and behavioural trends among riders. The societal implications of this approach extend beyond punitive measures. It cultivates civic responsibility and trust in law enforcement. By integrating artificial- intelligence-based detection algorithms in future iterations, manual verification efforts will be reduced, enabling authorities to allocate re- sources more strategically. Furthermore, the collected analytics will inform infrastructure planning, such as the placement of new traffic signals or awareness campaigns in high-risk areas. The synergy of technology and community engagement thus represents a sustainable evolution in road-safety management.

II. LITERATURE SURVEY

The evolution of intelligent traffic systems has been shaped by progress in computer vision, cloud computing, and par- ticipatory governance. A review of related work reveals the interdisciplinary nature of this domain.

K. Kotecha et al.[1] (2021) utilised convolutional neural networks (CNNs) trained on motorcyclist datasets to iden- tify helmetless riders in real-time video feeds. Their system demonstrated how automated detection can supplement human policing by achieving accuracy above 94 per cent on bench- mark datasets.

M. Faiz et al.[2] (2022) and Zhang et al. (2024) expanded the YOLO family of architectures (v5–v8) for small-object detection under challenging lighting and occlusion conditions. These studies form the technical foundation for the AI verifi- cation module proposed in this research.

J. Li et al.[3] (2020) introduced an IoT-enabled cloud architecture capable of handling heterogeneous traffic data. The concept of distributed edge processing ensures real-time responses with minimal latency— principles later incorporated into our design.

R. Kumar et al.[4] (2023) investigated gamified reward systems that motivate citizens to report civic issues. Their work validated that digital incentives significantly increase participation and sustain engagement over long periods.

T. Chen et al. [5] (2023) employed big-data analytics to generate road-risk heatmaps. Predictive algorithms derived from historical violation patterns were used to plan targeted interventions, providing the conceptual base for our analytics engine.

S. Gupta et al. [6] (2022) launched a crowdsourced road- safety monitoring system that runs on mobile networks. When people send in real-time reports, it's not just about catching more violations—city planners actually get the data they need to make decisions.

P. Vyas et al. [7] (2020) tried a different angle by adding gamified incentives. When you offer structured rewards, peo- ple jump in and report more issues. That matches up well with the reward system used in this project.

A. Singh et al. [8] (2021) combined Artificial Intelligence and IoT to build a road safety framework. Their work showed that sensors and smart algorithms really can do the heavy lift- ing—automating violation detection and making enforcement a lot smoother.

R. Mehta and P. Joshi [9] (2022) looked at the ethical and technical challenges of AI surveillance in smart cities. They zeroed in on privacy, transparency, and fairness—key ideas that influenced how this system stays secure and accountable.

D. Sharma [10] (2021) pushed mobile crowdsensing as a way to shape urban policy. The study proved that when you gather huge amounts of citizen data, smarter decisions about traffic and infrastructure follow. It's a strong case for large- scale, data-driven planning.

A. Patel et al. [11] (2022) used deep reinforcement learning to optimize traffic signals. Their results showed that smart controls really do cut congestion and keep traffic moving, which fits right in with this project's analysis tools.

L. Wang and M. Liu [12] (2021) built accident prediction models using big data from past traffic patterns. Their pre- dictive approach backs up the use of violation heatmaps and risk-zone maps in this research.

H. Kaur et al. [13] (2023) used blockchain to secure digital evidence for law enforcement. Their system keeps evidence tamper-proof and safe, showing a clear path for future up- grades to this platform.

B. Nair [14] (2020) examined the impact of citizen involve- ment on smart governance. The study showed that participation builds accountability and brings citizens and authorities closer together.

V. Prakash and S. Menon [15] (2023) addressed fairness and bias in AI traffic violation detection. They highlighted the need for unbiased datasets and open algorithms if you want enforcement that people can trust.

G. Sundar [16] (2022) developed cloud-based traffic moni- toring systems built to handle massive data loads. Their work laid the groundwork for the scalable cloud setup used in this project.

R. Varma et al. [17] (2021) used data-driven strategies to improve urban road safety. They found that analytics lead to smarter safety interventions and better infrastructure. K. Tan and L. Chen [18] (2023) focused on human-centered AI for public safety. Their research put usability, trust, and accessibility at the core, which helped shape the citizen-friendly design of this mobile app.

III. EXISTING SYSTEM

Traditional traffic enforcement mechanisms depend heavily on manpower and static infrastructure. Manual policing domi- nates rural and semi-urban regions, whereas urban centres rely on CCTV networks.

A. Manual Policing

Traffic officers visually monitor intersections and impose fines for violations. This approach offers directhuman judg- ment but suffers from subjectivity, limited scalability, and vulnerability to human fatigue or bias

B. CCTV Surveillance

Although closed-circuit cameras enhance coverage, their ef- fectiveness depends on placement, maintenance, and operator vigilance. Large-scale deployments face high installation costs and bandwidth limitations.

C. Limitations and Challenges

- Limited Coverage : Surveillance infrastructure is con- centrated in metropolitan regions, leaving rural areas unmonitored.
- Cost and Maintenance : High capital expenditure on hardware and software upkeep.
- Manual Verification : Video footage still requires human inspection to confirm offences.
- Data Isolation : No centralised repository integrating reports from citizens, cameras, and sensors.

Lack of Incentives : Citizens have no structured motiva- tion to report unsafe behaviour.

IV. PROPOSED SYSTEM

The proposed system introduces a comprehensive digital ecosystem that fuses mobile computing, cloud technology, and AI analytics to create a participatory enforcement model.

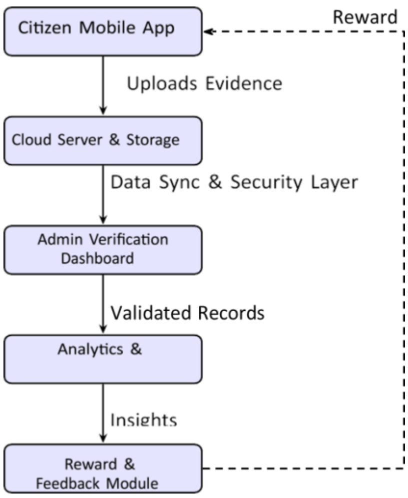

Fig. 1. Block Diagram of Proposed Community-Driven Enforcement System

A. Mobile Application Module

The Android and Flutter application enables users to capture geotagged photos or videos with a single tap. Each file is automatically stamped with the current time and location, encrypted prior to upload, and users' accumulated points are tracked within a reward wallet.

B. Cloud Infrastructure

A hybrid backend using Firebase and MySQL ensures low latency and real-time synchronisation. REST APIs authenticate users, store evidence, and forward metadata for analysis.

C. Administrative Dashboard

Authorities operate a web dashboard developed using Re- actJS and Flask. Through this interface, they can review and approve submitted evidence, monitor statistics for reports by location and time, and manage user access across different roles to support multi-level verification.

D. Analytics and AI Module

Python-based services use pre-trained YOLOv8 and OpenCV models to automatically detect helmets, signal colour, and license-plate regions. The analytics engine aggregates validated data to generate violation heatmaps, temporal graphs, and compliance trends.

E. Reward Mechanism

Each verified report grants reward points. Fraud detection filters duplicate or tampered uploads using perceptual hashing. Points are redeemable through partnered e-wallet APIs or telecom vouchers.

F. Workflow Summary

Figure 2 outlines the logical flow of activities within the system, highlighting user interaction and automated process- ing.

G. Advantages

- Expands enforcement coverage without heavy infrastruc- ture.
- Encourages citizen accountability and transparency.

Reduces operational costs while improving compliance.

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V. METHODOLOGY

The implementation of the community-driven enforcement platform was divided into sequential phases, each addressing a functional layer of the system. Agile methodology was adopted to ensure iterative development and feedback incorporation.

A. Phase 1 – Requirement Analysis

Interviews with local traffic authorities helped identify criti- cal pain points such as insufficient manpower, lack of real-time evidence, and data fragmentation. Citizen surveys highlighted a willingness to report violations if rewards and privacy were guaranteed.

B. Phase 2 – System Design

Interviews with local traffic authorities helped identify criti- cal pain points such as insufficient manpower, lack of real-time evidence, and data fragmentation. Citizen surveys highlighted a willingness to report violations if rewards and privacy were guaranteed.

C. Phase 3 – Mobile Application Development

The front end was developed using Flutter and leveraged camera APIs to capture metadata in real time. For user sign-in, Firebase Authentication manages everything, supporting both OTP and Google credentials. The data model is structured as follows: a User Table containing User ID, Name, Contact, and Reputation Score; a Report Table with Report ID, Image Path, Timestamp, Geo Location, and Status; and a Reward Table that records User ID, Points, and whether rewards have been redeemed.

D. Phase 4 – Backend Development

Flask REST APIs handle secure communication between the client and the database. JWT tokens maintain session in- tegrity. Cloud Functions automatically trigger image validation and AI inference.

E. Phase 5 – AI Detection Engine

A YOLOv8 model pretrained on 6,000 labeled images of motorcycles, and it detects helmets with a mean average precision of 0.92. Here's how the pipeline functions: it receives an uploaded frame, locates the rider, checks for a helmet, and draws a bounding box. If the model does not detect a helmet, it flags it as a violation.

F. Phase 6 – Reward Module

Once an admin approves a report, Firebase Cloud Mes- saging sends an instant acknowledgement. Reward points are updated in the user wallet and can be redeemed via a simple UPI or voucher API.Firebase Cloud Messaging used.

G. Phase 7 – Testing

Black-box and white-box testing were applied. Stress tests verified that the system sustained 500 simultaneous uploads without timeout. Penetration tests confirmed protection against injection and replay attacks.

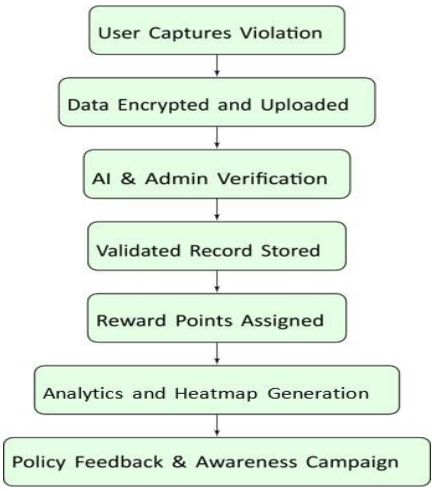

Fig. 2. Workflow Diagram of Proposed System

VI. SYSTEM MODEL

The implementation of the community-driven enforcement platform was divided into sequential phases, each addressing a functional layer of the system. Agile methodology was adopted to ensure iterative development and feedback incorporation.

A. System Architecture

This application is divided into two core components: the client and the server. On the client side, a Flutter Android app lets users take photos and submit violation reports. The server side runs on Flask (Python) and serves dual purposes—it provides the API for the mobile app and powers the Admin Dashboard on the web. All data is stored in a SQLite database managed with SQLAlchemy, which ensures users, reports, and rewards are persistently and neatly organized.

B. Backend Technologies(Flask)

Flask is the foundation of the backend. It's lightweight, quick to set up, and manages all incoming web requests. SQLAlchemy handles object-relational mapping, so Python classes like User, Report, and Reward become database tables without needing raw SQL. The Admin Dashboard pages are rendered using Jinja2, letting the server inject data dynam- ically. For image processing—such as resizing, sharpness checking, or prepping for AI analysis—the code uses OpenCV and NumPy. The flask-cors library is included, allowing the mobile app to communicate with the backend even across separate devices.

C. AI & Computer Vision Implementation

The platform relies on a hybrid AI system for dependability.

1) Primary Analysis (Generative AI - Google Gemini): Most analysis is handled through Google's Generative Lan- guage API. The application makes REST calls directly to Google's AI models. If a model is unavailable or fails, a fallback sequence is in place: it retries with the next model in order—gemini-2.5-flash-preview (top choice), then gemini- 2.0-flash, followed by gemini-2.0-flash-lite, and finally gemini- 1.5-flash (most stable). To keep responses predictable and easy to interpret, all prompts are packaged in structured JSON, requesting details like helmet or vehicle presence, image quality scoring, and reward calculation.

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2) Secondary Analysis (Local Computer Vision - OpenCV): If all AI requests fail—due to network issues or hitting usage limits—the system defaults to local image processing. It uses Laplacian variance to evaluate blur. For helmet and vehicle recognition, it filters images in HSV color space and searches for contours that match the expected shapes of helmets or vehicles.

D. Mobile Application (Flutter) State Management

State in the mobile app is managed with the Provider pat- tern. Auth Provider monitors authentication status, registration, and user profile tokens. Report Provider manages everything related to submitting reports, handling errors, uploads, and retrieving previous reports. The image picker package is used to open the Android camera for taking photos. geo locator fetches precise latitude and longitude, while reverse geo coding converts this into a readable address for display. All network operations use the http package, sending both images and report details in a single POST request.

E. Database Schema

User records store authentication details, user/admin roles, and accumulated rewards. Reports link each user to a violation entry and include the image path. Location details consist of latitude, longitude, and address. Rewards log every point transaction in a user's wallet. Redemptions record requests to exchange points for items like mobile top-ups or coupons.

F. Security Features

For admins, session management is handled on the server side. API authentication uses Bearer Tokens in the HTTP header. The backend verifies every uploaded file to ensure it's a valid image and not excessively large. As for rate limiting, the AI fallback system addresses it—if one model is rate- limited, the application automatically attempts the next model in sequence.

VII. RESULTS AND DISCUSSION

Pilot deployment across three traffic zones in Coimbat- ore.The quantitative outcomes of the pilot deployment indicate promising results. In addition to monitoring changes over time, the team developed spatial heatmaps by collecting data from various locations around Coimbatore. These heatmaps highlight the areas with the highest concentration of traffic violations, essentially pinpointing the city's trouble spots. To make this happen, people submitted real-time reports using the mobile app, covering both busy city centers and quieter outskirts.

Areas such as Gandhipuram, Saravanampatti, Sitra, R.S. Puram, Saibaba Colony, G.N. Mills, Ganapathy, Singanallur, Keeranatham, and Periyanaickenpalayam emerged as hotspots.

A. Quantitative Outcomes

A total of 512 reports were submitted, of which 381 were verified as genuine, representing an accuracy rate of 83.3 %. The average verification time per report was 45 seconds, demonstrating efficient processing. Helmet usage increased by 19.6 % in the target areas during the study period. Addition- ally, the system achieved a user retention rate of 87 % after two weeks, indicating sustained user engagement.

B. Performance Evaluation

The AI engine processed each frame in 0.18 seconds on average using a mid-range GPU. The cloud database achieved 99.8 % uptime.

C. Data Analytics

Heatmaps generated from 15 days of data revealed peak violations between 17:00 and 20:00 hours, particularly near commercial corridors.

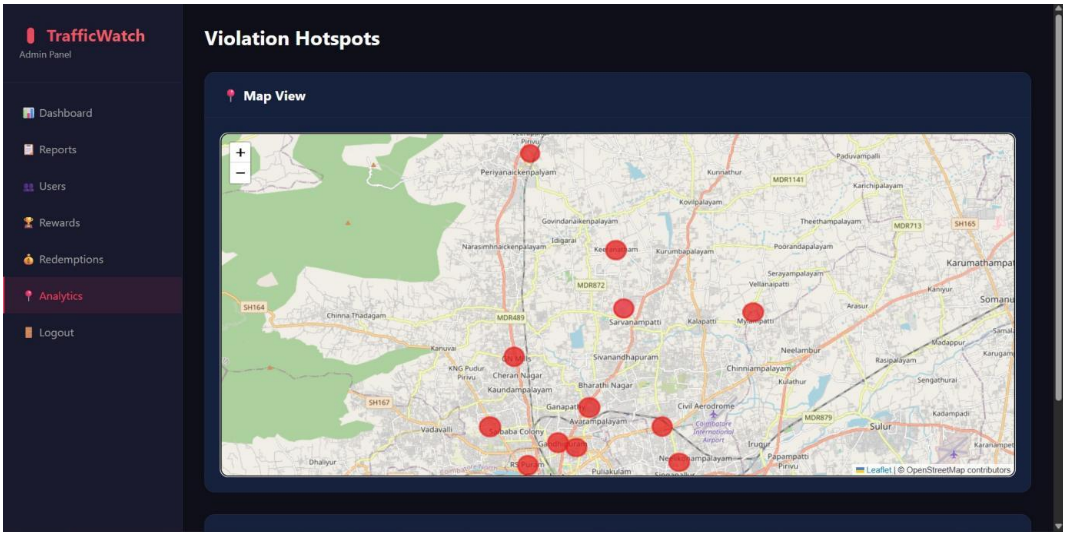

Fig. 3. Screenshot of Analytic Heat Map

This isn't too surprising—these neighborhoods experience heavy traffic, have lots of commercial activity, and feature major intersections, which leads to more violations being reported. With this heatmap, traffic officials can clearly see where to concentrate their efforts. They can increase patrols, run focused awareness campaigns, or adjust signals and signage in these high-risk zones. Moreover, the results show that the community reporting system is effective, it's capturing traffic violations exactly where they occur, throughout Coimbatore.

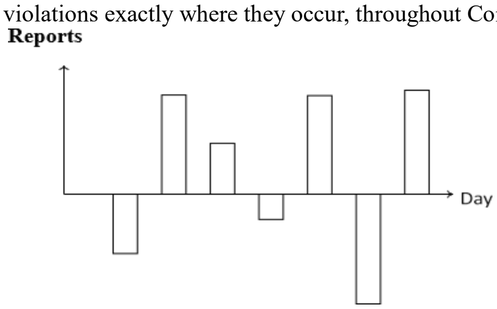

Fig.4. Sample Weekly Report Submission Chart

VIII. FUTURE ENHANCEMENT

- AI Expansion
- Predictive Analytics
- IoT Integration
- National Adoption Blockchain Logging

IX. CONCLUSION

The Community-Driven Traffic Law Enforcement with Re- ward Mechanism project demonstrates how citizen engage- ment, when coupled with modern computing, can revolutionise road safety. By leveraging mobile connectivity and cloud infrastructure, the model bridges the gap between public par- ticipation and government authority. The prototype validates that decentralised evidence collection is feasible, secure, and motivating when accompanied by transparent rewards. With continuous refinement—particularly the evidence integrity in- tegration of AI and predictive analytics—this initiative can evolve into a nationwide digital enforcement network, sup- porting the broader goals of India's Smart City Mission and Sustainable Development Goal 3.6 (halving road traffic deaths).

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