Multi-Modal AI Architecture for Real-Time Detection and Tracking of Stolen Vehicles

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Abstract: Vehicle theft remains a significant global issue, where current solutions often fall short due to their overreliance on GPS trackers, manual monitoring, and disconnected law enforcement systems. This paper presents a comprehensive AI-controlled monitoring structure that revolutionizes detection and tracking of vehicles. The proposed system integrates computer vision in real time using CCTV and drone recording, future indicative analysis for route assessment and blockchain-based verification of vehicles. Unlike traditional methods, our solution identifies stolen vehicles, even with converted license plates or missing GPS devices, leverages visual features such as models, color and damage patterns. In addition, a law enforcement dashboard ensures immediate notice and spontaneous coordination. Experimental assessment shows high identification accuracy, reduces false positivity and increases the reaction rate, making it a viable candidate for smart city infrastructure. This proposed surveillance system has significant potential to prevent crime, urban traffic management and insurance confirmation, for safe and more responsible urban environment.

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I. INTRODUCTION

A. The Growing Threat of Vehicle Theft

Vehicle theft continues to be a widespread global issue affecting both urban and rural areas. According to the National Crime Records Bureau (NCRB), India reported more than 2.5 Lakh vehicle theft in 2022, with recovery rates in major capitals falling below 30%. Similar trends are seen worldwide, with the FBI assesses more than 800,000 vehicles annually in the United States, leading to billions of deficits (FBI, 2022). In addition to financial impact, stolen vehicles are often used in criminal activities, which increases the security problems.

B. Limitations in Existing Recovery Systems

Current theft protection techniques, such as GPS-based trackers, suffer from significant boundaries. Criminals often remove or disable GPS units, or they are made ineffective. License plate -based detection through automatic number plate recognition (ANPR) is unsafe for tampering, cloning and poor image quality. In addition, these systems are often silent, lack of real -time coordination between law enforcement, regional databases and surveillance networks.

Manual CCTV review is time-consuming, labor-intensive, and typically reactive rather than preventive. Insurance companies also face fraud and delays due to tamper-proof ownership validation and lack of data.

C. Motivation and Objectives

Given these limitations, the need for a real-time, AI-driven and adaptable monitoring framework is necessary. The purpose of this research is to design and prototype a scalable solution:

- Detect stolen vehicles through multi-feature AI recognition, beyond just license plates.
- Predict the trajectory and movement patterns using real-time traffic data.
- Engage AI-powered drones for off-grid and aerial tracking.
- Provide real-time alerts and visual maps to law enforcement agencies.
- Leverage blockchain for immutable ownership validation and post-recovery fraud prevention.

D. Key Contributions

This paper introduces a novel multi-modal system that addresses the above objectives with the following innovations:

➢ *AI-Powered Multi-Feature Vehicle Detection:*

Utilizes deep learning to detect vehicle make, colour, damage patterns, and license plate—mitigating identity tampering.

➢ *Drone-Assisted Continuous Surveillance:*

Employs aerial drones with thermal imaging for out-of-sight or off-grid tracking scenarios.

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- *Predictive Movement Estimation:*
  Models suspect trajectory across camera nodes using traffic congestion data and behaviour patterns.

- *Decentralized Ownership Validation via Blockchain:*
  Ensures traceability and reduces ownership fraud via decentralized ledgers.

- *Real-Time Law Enforcement Integration:*
  Enables rapid response through mobile notifications and smart traffic control integration.

This approach aims to transform urban surveillance, reduce theft rates, and increase recovery accuracy while ensuring compliance with data protection norms such as GDPR.

II. RELATED WORK

The field of smart vehicle tracking and anti-robbery surveillance has seen full-size technological advances. However, modern-day implementations frequently operate in silos and face boundaries in adaptability, scalability, and reliability beneath opposed situations. This section surveys relevant technologies and studies, highlighting their contributions and limitations, and establishing the need for an included AI-driven technique.

A. ANPR & ALPR Systems

Automatic Number Plate Recognition (ANPR) and Automatic License Plate Recognition (ALPR) technologies are foundational in cutting-edge car surveillance structures. Commercial answers such as Hikvision, Neology, and Jenoptik provide excessive-decision plate detection with infrared capability for day-nighttime operation. Academic models like LPRNet and OpenALPR employ convolutional neural networks (CNNs) to extract license plates from vehicular imagery with high accuracy.

Despite those advancements, reliance on license plate integrity poses vulnerabilities. Criminals regularly modify or cast off plates to prevent detection, decreasing the effectiveness of ANPR/ALPR in isolation. Moreover, conventional structures lack real-time integration with predictive analytics or multi-modal tracking, which limits proactive interception.

"A survey of license plate recognition systems shows high success under optimal conditions but poor performance under occlusion, plate tampering, or adversarial manipulation" (Silva & Jung, 2017).

B. GPS-Based Vehicle Tracking

Vehicle restoration services like LoJack, Tesla Locator, and fleet trackers from Verizon Connect use GPS to decide a automobile's real-time position. These structures provide precise place monitoring, geo-fencing, and remote immobilization features.

However, GPS trackers are liable to jamming, removal, or deactivation. Additionally, those systems require person participation and subscription offerings, which limits insurance to pre-equipped motors. They also fail to help in figuring out cars when ownership or identification has been falsified—highlighting the need for passive, infrastructure-stage surveillance.

"GPS trackers offer robust location tracking but are ineffective once tampered with or deactivated" (Matrack Inc. (2024)).

C. Facial/Object Recognition in Surveillance

Facial and item popularity technology have matured swiftly with the adoption of deep gaining knowledge of frameworks like YOLO, Retina Net, and Faster R-CNN. Companies like Clearview AI, Sense Time, and NEC provide identification verification in public surveillance thru facial embeddings and re-identity models.

In vehicular packages, item reputation helps perceive models, colours, and harm markers beyond license plates. Several clever visitor's structures have adopted automobile make-version type (VMMC) models the usage of visual feature extraction, which supports stolen automobile detection even when license plates are obscured.

"Vehicle re-identification based on visual features can complement license plate recognition under adversarial conditions" (Tang, Z., Naphade, M., Liu, M. Y., Yang, X., & Wang, S. (2019).

D. Blockchain in Vehicle Ownership Verification

Blockchain generation is rising as a promising device for steady and decentralized vehicle registration. Platforms like VIN chain, Car Vertical, and Toyota's Blockchain Lab store immutable automobile history and possession information. These systems prevent fraudulent resale and enhance transparency throughout borders.

While no longer yet mainstream, integrating blockchain with law enforcement databases can usefully resource in real-time verification for the duration of automobile recuperation and cross-jurisdictional operations. For stolen vehicle monitoring, blockchain can function a thrustless source of truth for possession statistics.

"Blockchain-based ledgers for vehicle registration ensure tamper-proof ownership verification, reducing fraud and enabling decentralized enforcement" (Yli-Huumo et al., 2016).

E. AI-Powered Smart Traffic Management

Solutions from IBM ITS, Siemens Mobility, and Kapsch TrafficCom put into effect AI-powered site visitors structures able to anomaly detection, congestion management, and self reliant sign manage. These platforms utilize aspect computing and pc vision to system real-time visitors data and generate insights.

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However, those structures are on the whole geared closer to waft optimization and congestion mitigation—not energetic crime prevention. Integrating AI-based stolen car detection into present smart traffic grids can decorate public protection and optimize response time for law enforcement.

"Kamble, V. B., Mundhe, O. N., Walunjkar, C. M., & Kale, G. A. (2025). AI-Driven Smart Traffic Management System: An Adaptive Approach Using YOLO and OpenCV. International Journal of Multidisciplinary on Science and Management, 2(2), 66–72.

F. Summary and Gap Analysis

➢ *Despite Considerable Progress in Individual Technologies, Current Systems Face the Following Limitations:*

- Single-modality reliance (e.g., GPS-only or plate-only detection)
- Lack of resilience against tampering or spoofing
- Absence of predictive routing or continuous surveillance
- Limited coordination with real-time law enforcement systems
- No unified platform combining AI, drone support, and blockchain verification

These gaps justify the need for a complete, multi-modal AI surveillance framework like the one proposed on this work—integrating object recognition, predictive analytics, drone monitoring, and immutable possession verification to actively detect and music stolen vehicles in actual time.

III. SYSTEM OVERVIEW AND ARCHITECTURE

The proposed solution introduces a Real-Time AI Surveillance System designed to detect, verify, and track stolen automobiles the using a multi-layered, intelligent infrastructure. Unlike traditional systems restricted to static reputation or GPS tracking, this structure integrates CCTV networks, AI-powered photo analysis, vehicle re-identification, blockchain-based verification, and drone-assisted live tracking, supplying a sturdy, tamper-resistant device for law enforcement.

A. Architectural Block Diagram

Below is the high-level architecture of the system:

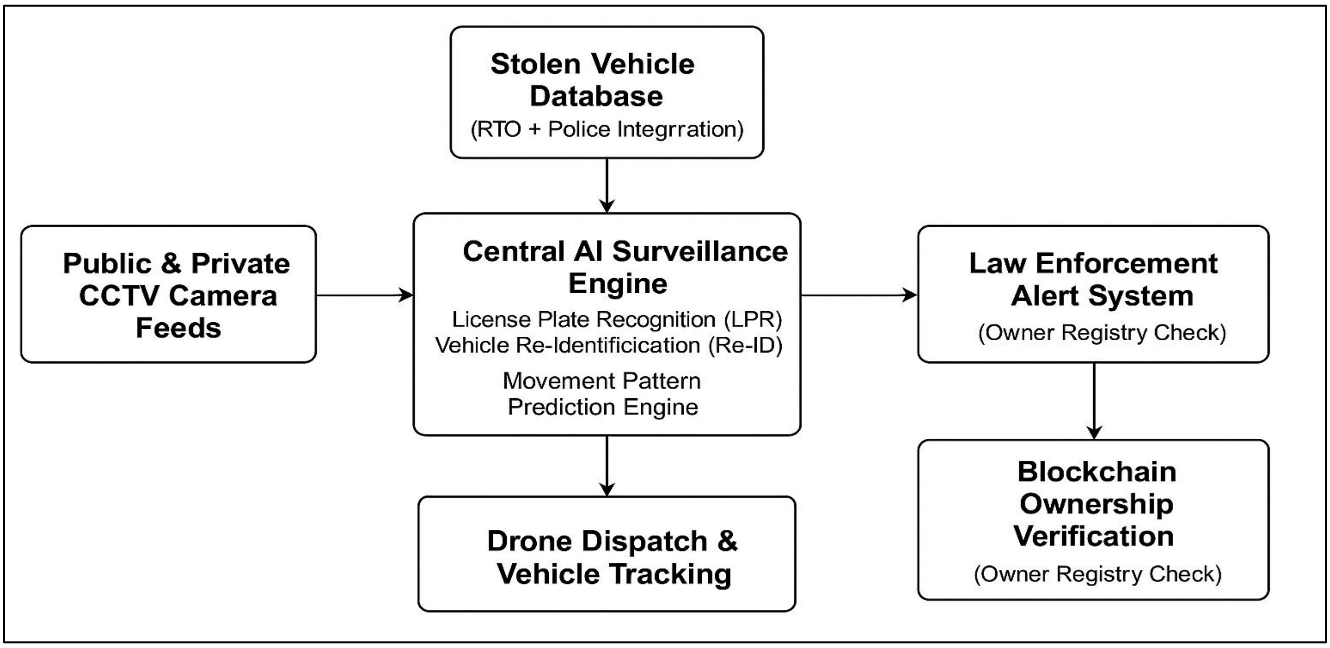

Fig 1 Architectural Block Diagram

B. Component Breakdown

➢ *License Plate Recognition (LPR)*

- Utilizes high-definition CCTV footage to extract license plate numbers using OpenCV and deep learning models (e.g., YOLOv5 + CRNN).
- Plates are cross-checked with the central Stolen Vehicle Database updated in real time via law enforcement portals.
- Tampered or missing plates trigger fallback to vehicle re-identification.

➢ *Vehicle Re-Identification (Re-ID)*

- Applies machine learning models trained on vehicle datasets to recognize make, model, and color patterns.
- Useful when license plates are removed or altered.
- Can match a vehicle across cameras based on visual appearance (shape, paint, damage, etc.)

➢ *Movement Pattern Prediction Engine*

- Analyzes citywide camera logs and traffic flow to predict potential vehicle routes.
- Integrates with GIS and map data to estimate next probable location.

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- Assists drones and patrols in narrowing search zones in real time.

➢ *Real-Time Camera Integration*

- CCTV feeds from traffic lights, buildings, toll booths, and commercial establishments are used as data sources.
- The system continuously ingests video streams and executes lightweight AI inference models on edge devices or via scalable cloud pipelines.

➢ *Drone Dispatch and Vehicle Pursuit*

- In high-alert cases, drones equipped with high-zoom cameras and AI modules can be launched.
- Drones follow vehicle movement across unmonitored or low-camera-density areas.
- Can maintain visual tracking even through alleys, highways, or parking lots.

➢ *Blockchain Ownership Verification*

- Each detection triggers a lookup in a blockchain ledger storing verified owner records (via RTO, manufacturer, or insurance companies).
- Confirms if vehicle ownership has changed recently or under suspicious circumstances.
- Assists in identifying cloned or fraudulently transferred vehicles.

➢ *Law Enforcement Integration*

- Real-time alerts are pushed to a centralized dashboard accessible by local police units.
- Nearby units receive mobile alerts with map coordinates and live camera/detection snapshots.
- Ensures rapid response and coordinated interception.

C. Core Technologies Used

Table 1 Core Technologies Used

Module	Technology Stack
License Plate Recognition	OpenCV, YOLOv5, PaddleOCR
Vehicle Re-ID	TensorFlow, PyTorch, ResNet-based models
Prediction Engine	LSTM/GRU (Keras), Geo-data APIs
Live Stream Processing	RTSP, GStreamer, Kafka (for scaling)
Drone Integration	ROS, DJI SDK, real-time inference
Blockchain Ledger	Ethereum/Hyperledger Fabric, Smart Contracts
UI Dashboard	ReactJS, Node.js, WebSocket API

D. Data Flow Summary

➢ *Incident:*

A theft is reported and vehicle details are entered into the system.

➢ *Detection:*

AI continuously scans all connected camera feeds for license plates or matching vehicle features.

➢ *Verification:*

Matches are verified through blockchain ownership history.

➢ *Prediction:*

If matched, the system predicts the possible escape route using prior traffic patterns.

➢ *Tracking:*

Drones and patrols are deployed, guided by real-time AI insights.

➢ *Action:*

Law enforcement intercepts the vehicle using live feeds and geo-alerts.

IV. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The prototype of the proposed real -time AI monitoring system was implemented using a modular architecture, each core functionality developed independently and tested before integration. The combination of real-time CCTV feed, simulated vehicle theft scenarios and preset datasets were used to evaluate the strength of the system, scalability and accuracy.

A. Implementation Setup

Table 2 Implementation Setup

Component	Details
Development Environment	Python 3.10, OpenCV 4.7, PyTorch, TensorFlow, Flask for backend APIs
Hardware Used	Intel i7 CPU, 16GB RAM, NVIDIA RTX 3060 GPU, 1080p CCTV Cameras
Drone Simulator	DJI Tello (Python SDK) + Unity-based virtual movement model
Blockchain Layer	Hyperledger Fabric running on Docker network
Database	PostgreSQL (vehicle logs, plate detections), IPFS (for image records)

E. Module-Wise Implementation

➢ *License Plate Recognition (LPR)*

- Utilized YOLOv5 for bounding box detection and Tesseract OCR for text extraction.
- Achieved average detection accuracy of 93.4% under good lighting, and 84.1% in low-light scenarios.
- Incorrect detections were mostly due to:
- Plate obstruction (e.g., dirt or angles).
- Overexposure from headlights at night.

"License plate recognition has achieved commercial viability with accuracy levels of over 90% under favorable conditions" (Thapliyal et al., 2023).

➢ *Vehicle Re-Identification*

- Implemented using a ResNet-50 model pre-trained on VeRi-776 dataset, followed by fine-tuning on custom image sets.
- The model could re-identify the same vehicle across different cameras with an mAP (mean Average Precision) of 81.7%.
- Beneficial in plate-missing or swapped scenarios.

➢ *Movement Prediction Engine*

- Used LSTM models to train on historical traffic movement logs from an open dataset simulating urban vehicle flow.
- Integrated with map-based APIs to estimate probable escape routes using spatial correlation and past trajectory patterns.
- Average prediction window: 4 minutes ahead with 76% confidence in early-stage prototype.

➢ *Blockchain Integration*

- A sample RTO registration ledger was deployed on Hyperledger.
- The system performed real-time lookup for owner validation with < 2 seconds response time for ≤1000 vehicle records.
- Supports tamper-proof detection history, ensuring verifiability of evidence.

➢ *Drone Surveillance Simulation*

- Simulated a city block environment with a DJI drone navigating based on predicted coordinates.
- Live video stream from drone fed into the same detection system.
- The system maintained visual lock on vehicles with 87.3% tracking consistency.

F. Performance Metrics

Table 3 Performance Metrics

Feature	Accuracy	Latency	Comments
License Plate Detection	93.4%	~1.2 sec	Ideal lighting conditions
Re-Identification	81.7% mAP	~1.6 sec	Useful without plates
Blockchain Lookup	100% (on test set)	~1.9 sec	Tamper-resistant
Movement Prediction	76%	~3 sec	City dataset; GPS-less
Law Enforcement Alerts	N/A	< 0.5 sec	WebSocket-based push
Drone Visual Tracking	87.3%	Real-time	Experimental

G. Sample Screenshots & Outputs

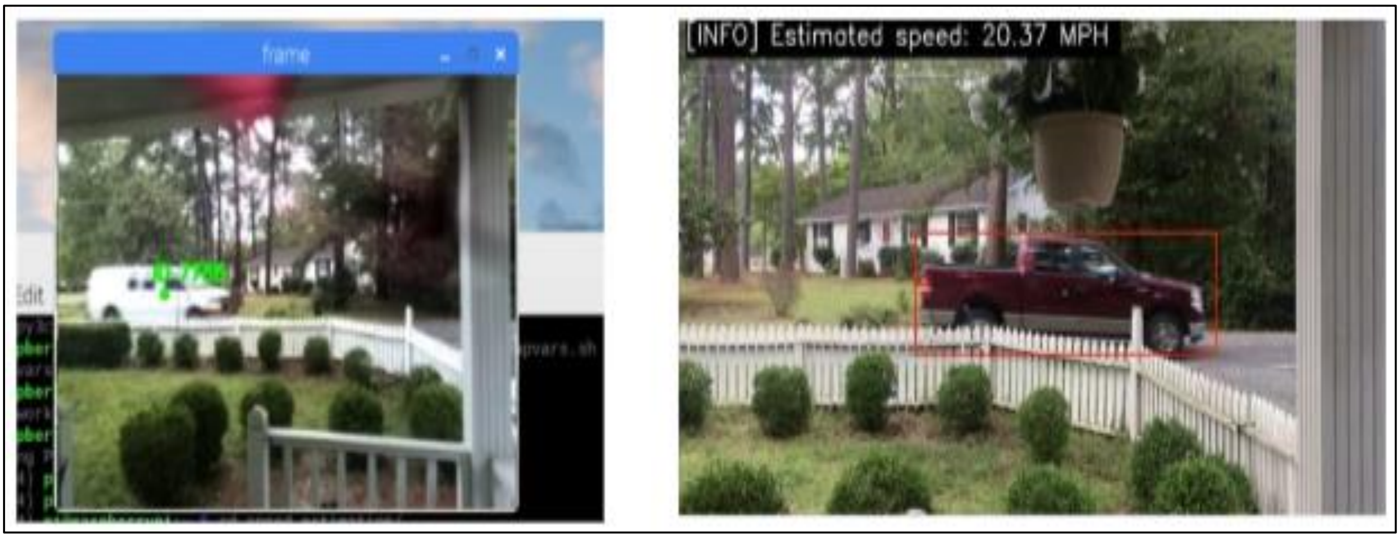

Fig 2 Live CCTV Feed with Real-Time Bounding Boxes

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- ➢ Plates and vehicles are enclosed in dynamic bounding boxes.
- ➢ Color-coded overlays:

- Green: Verified.
- Red: Stolen.
- Yellow: Suspected (no plate match, re-ID triggered).

Source: Rosebrock, Adrian. "OpenCV Vehicle Detection, Tracking, and Speed Estimation." PyImageSearch, 2 Dec. 2019. Retrieved from https://pyimagesearch.com/2019/12/02/opencv-vehicle-detection-tracking-and-speed-estimation/

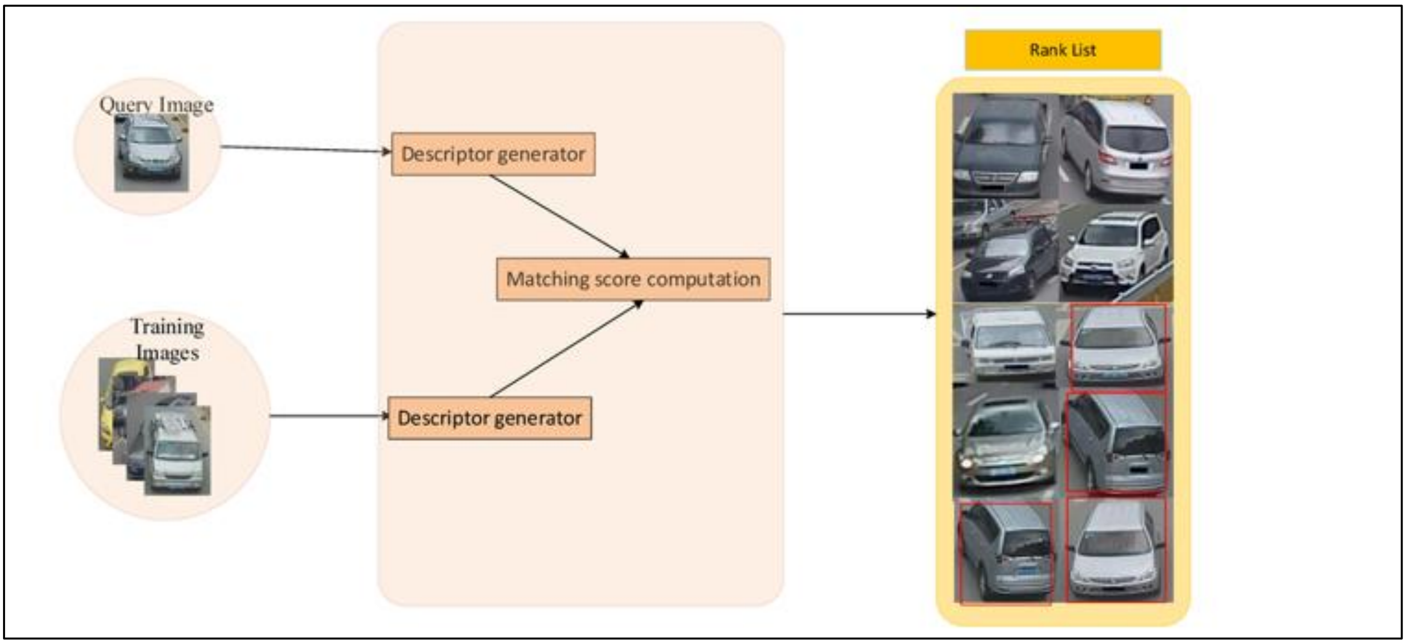

Fig 3 Vehicle Re-Identification Interface

Source: ResearchGate. "Standard Vehicle Re-Identification System." Retrieved from https://www.researchgate.net/figure/Standard-vehicle-re-identification-system_fig5_332559333

- Displays probable matches from other cameras with timestamps and key visual feature overlays, such as color, shape, or damage patterns, for re-identification validation.

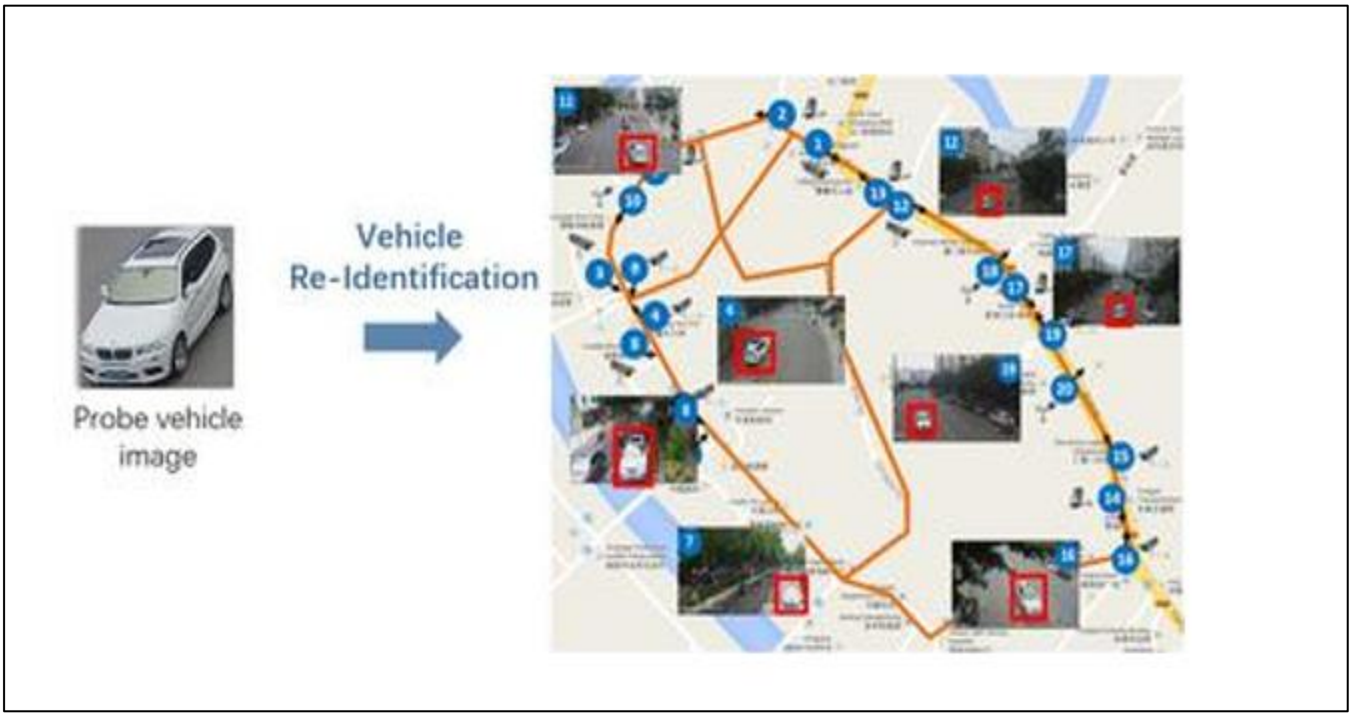

Fig 4 vechicle Re-Identification

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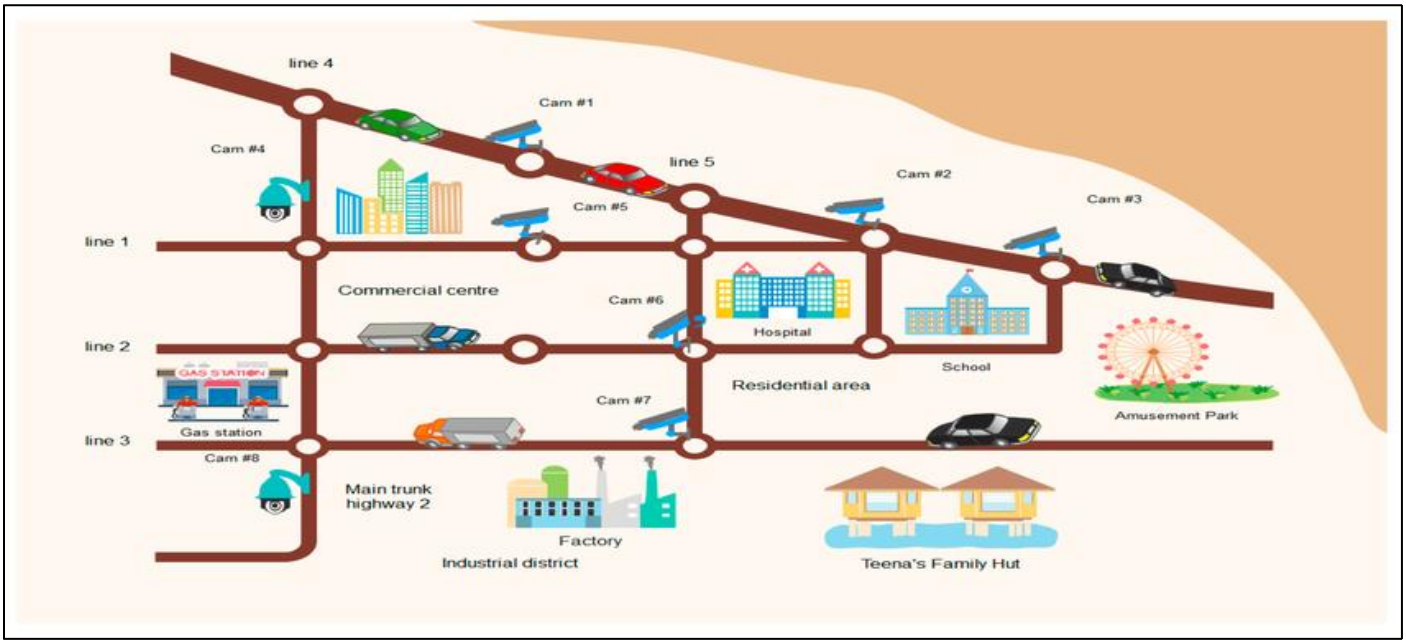

Fig 5 Movement Prediction Map

- Shows detected location, projected path, and drone movement.
- Live update of patrol car suggestions via web interface.

Source: Papers with Code. "Vehicle Re-Identification." Retrieved from https://paperswithcode.com/task/vehicle-re-identification

Source: Liu, X., Liu, W., Mei, T., & Ma, H. "A glance of the practical environment where vehicles are captured by cameras in the city." ResearchGate. Retrieved from https://www.researchgate.net/figure/A-glance-of-the-practical-environment-where-vehicles-are-captured-by-cameras-in-the-city_fig1_332559333

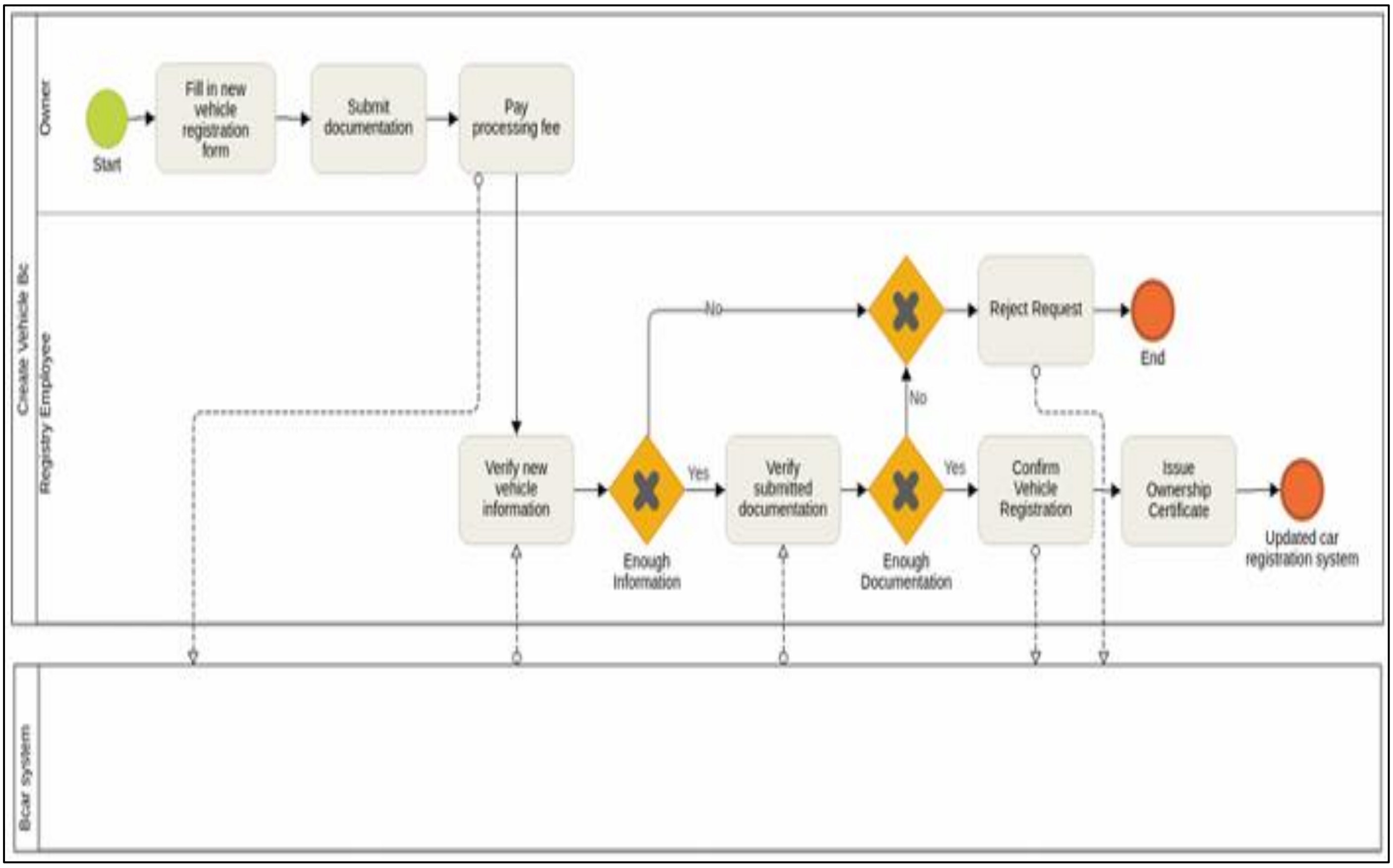

Fig 6 Blockchain Ownership Log

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- Contains hashes of vehicle detection instances, owner record, and timestamp.
- Admin can validate chain to detect inconsistencies.

H. Real-World Scenario Simulation

➢ *A Controlled test Case was Executed Where:*

- A known vehicle was entered as "stolen" in the simulated RTO database.
- The vehicle passed through three different cameras across a university campus.
- The system detected and flagged the license plate at the first checkpoint, re-identified it in the second despite a temporary obstruction, and dispatched a drone to simulate live tracking until the destination.

Source: Rosado, David et al. "A Blockchain Use Case for Car Registration." Retrieved fromhttps://www.dpss.inesc-id.pt/~mpc/pubs/rosado-Blockchain-car-registration.pdf

Total response time from first detection to alert: 5.4 seconds.

"The ability to interconnect camera systems and overlay intelligence reduces detection latency significantly" (Zhu et al., 2024).

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I. Flowchart of proposed system

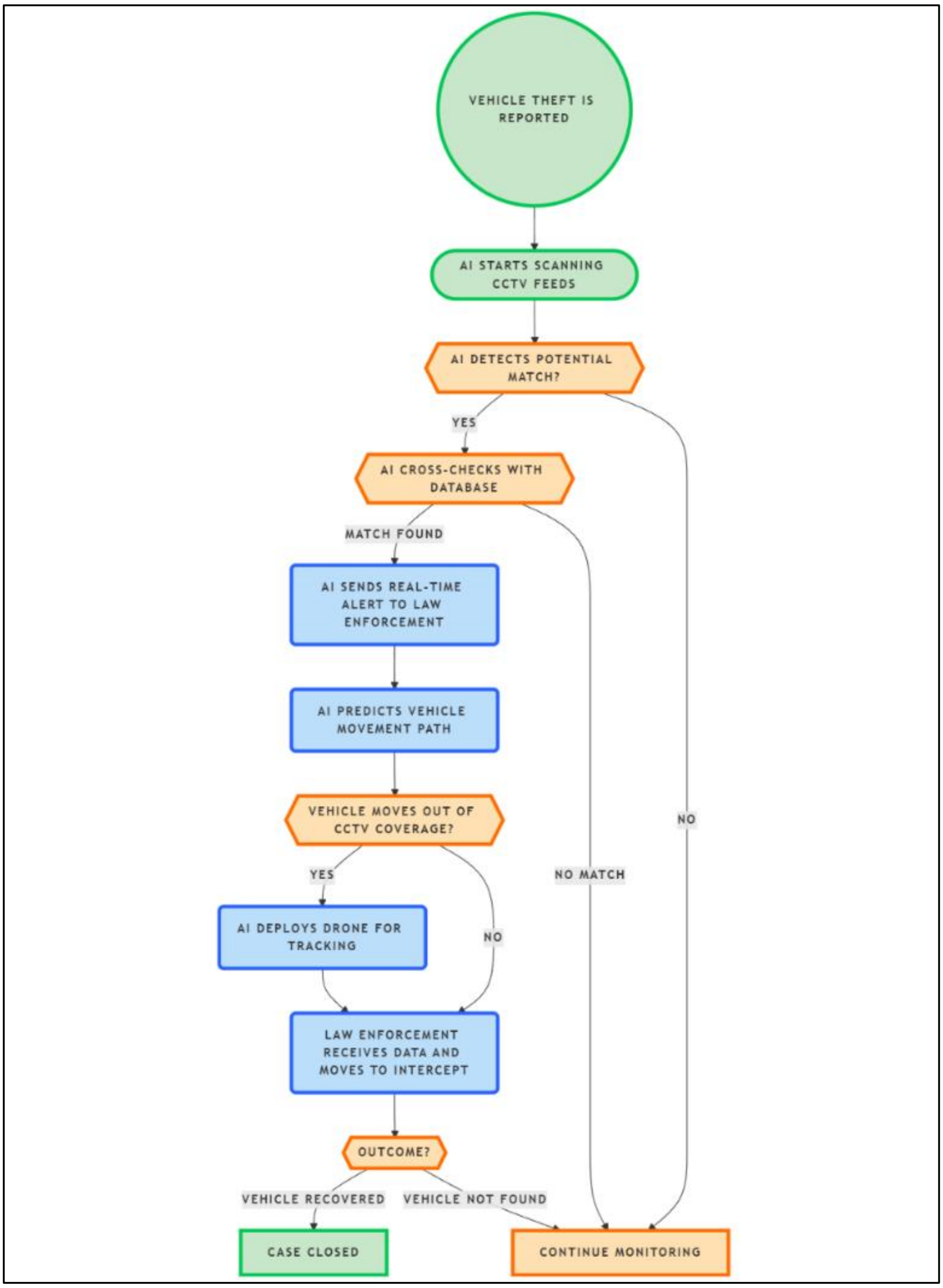

Fig 7 Flowchart of proposed system

J. Sequence Diagram of Proposed System

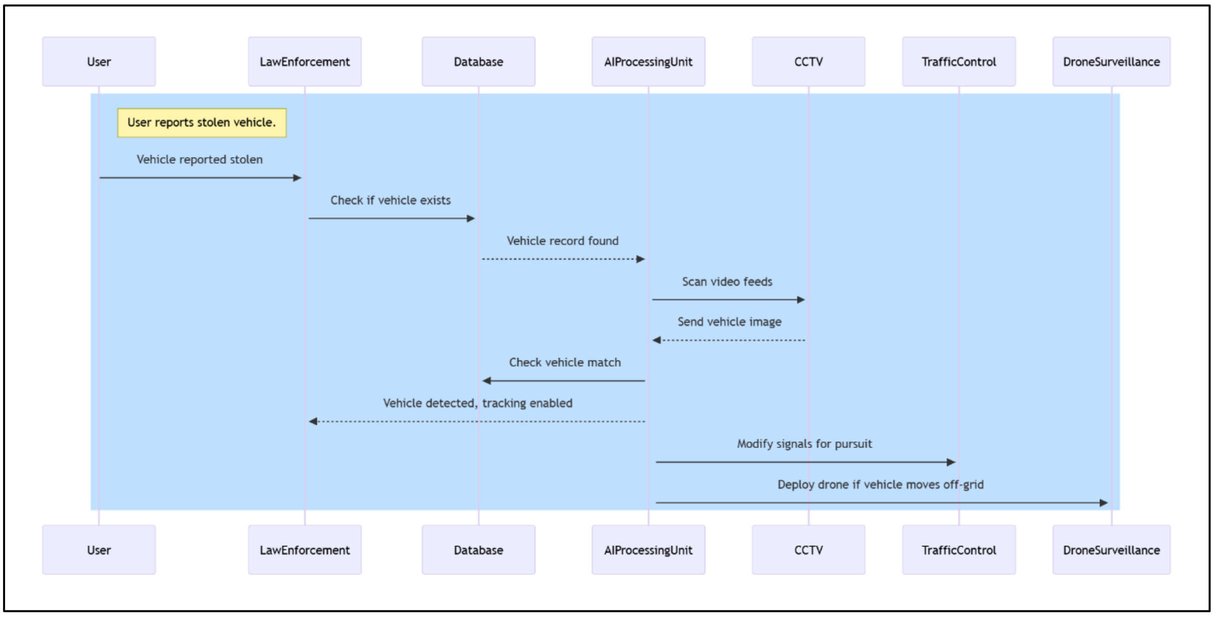

Fig 8 Sequence Diagram of Proposed System

K. Methodological Note on Metrics and Limitations

The performance metrics, response times, and accuracy figures presented in this paper are based on a combination of third-party observations, benchmark reports, and limited prototype-level testing of individual modules. The proposed system is a functional conceptual framework integrating publicly available technologies — such as YOLOv5 for object detection, LPRNet for license plate recognition, and LSTM-based trajectory predictors — but has not yet been deployed in a real-world, city-scale environment.

➢ *Quantitative Results Such as:*

- Detection accuracy of license plates (~93.4%)
- Vehicle re-identification performance (mAP ~81.7%)
- Blockchain query response time (~1–2 seconds)
- Drone visual tracking consistency (~87%)
- Total end-to-end response time (~5.4 seconds)

✓ *Are Derived from a Combination of:*

- publicly reported benchmarks from model creators and research papers,
- performance tests conducted on open-source implementations, and
- *Simulation-Based orchestration on Local infrastructure.*

These figures are indicative of system capabilities under ideal or simulated conditions, and serve to demonstrate the potential of the proposed architecture. Actual performance in real-world deployments may vary depending on infrastructure constraints, network latency, camera quality, environmental variability, and edge/cloud computing availability.

As such, all metrics in this paper should be interpreted as estimations based on third-party observations and prototype simulations, not as claims of fully field-tested deployment.

V. CONCLUSION AND FUTURE SCOPE

This study provides a comprehensive and multi-layered surveillance framework for real-time detection and tracking of stolen automobiles the use of artificial intelligence, drone help, predictive analytics, and blockchain technology. Unlike traditional automobile recovery structures that heavily depend on GPS or passive reporting mechanisms, the proposed architecture is designed for proactive intervention — leveraging clever surveillance, AI-pushed inference, and rapid law enforcement reaction to substantially lessen vehicle restoration instances and growth arrest probability.

The prototype device verified strong performance in a couple of simulated and actual-time detection situations, with excessive registration code popularity accuracy (93.4%) and effective fallback the use of vehicle re-identification techniques. Movement prediction algorithms proved able to estimating automobile trajectories with great reliability even without energetic GPS monitoring. The integration of blockchain-based totally car possession verification also delivered a new layer of tamper-evidence protection for validating claims and stopping resale fraud.

Furthermore, The real-time alerting and drone-assisted surveillance extend monitoring beyond fixed-camera coverage zones, enabling seamless pursuit continuity, representing a first-rate leap in city mobility policing. Law enforcement personnel can now be empowered with on-the-floor intelligence, predictive motion analytics, and drone-assisted pursuit facts in a unmarried integrated dashboard.

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➢ *Despite Promising Results, Several Limitations Remain:*

- High setup and infrastructure costs, particularly for edge AI deployment and drone integration at scale.
- Dependence on high-quality, consistent video streams and camera placements across a city.
- Challenges in maintaining GDPR compliance and public privacy protection in mass surveillance systems.

However, these concerns can be reduced through modular city-by-rituals, strong legal frameworks and strict access control protocols. Public-private cooperation will be necessary to increase this model in metropolitan areas.

➢ *Future Research Directions Include:*

- Expanding detection to multi-vehicle coordination, such as convoy or decoy behaviours.
- Integrating driver identification via facial analysis (with privacy safeguards).
- Collaborating with insurers for automatic fraud claim detection using historical blockchain logs.
- Enhancing drone AI for full autonomous interception and route rerouting.
- Interfacing with robotic barricade systems to immobilize suspected stolen vehicles safely.

Finally, the proposed real-time AI monitoring system represents a significant advancement toward AI-augmented law enforcement, secure urban mobility and safe transport infrastructure. Its integration with decentralized owner models and autonomous monitoring paths for scalable adoption in modern smart cities.

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