iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80955

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

DumpWatch AI: An Automated Illegal Dumping Detection System Using YOLOv8 and Vision Language Model Verification

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Abstract: ***Illegal dumping of waste in unauthorized locations poses serious environmental, public health, and urban management challenges. Conventional CCTV-based monitoring relies on manual review, which is time-consuming, inconsistent, and impractical for large-scale deployment. There is a growing need for automated, intelligent systems that can detect dumping events in real time without human intervention. This paper presents DumpWatch AI, an automated surveillance system designed to detect illegal dumping incidents in CCTV footage. The system employs YOLOv8 [1], a state-of-the-art real-time object detection model, to track persons, vehicles, and potential waste objects across video frames. A temporal persistence logic identifies objects that remain stationary at a location for more than five seconds after the associated person or vehicle has departed, flagging them as potential dumping events. To reduce false positives and enrich incident data, flagged frames are submitted to Gemini 2.0 Flash [2], a Vision Language Model (VLM), which performs semantic reasoning to classify the event type (Household, Industrial, Furniture), assess severity (LOW, MEDIUM, HIGH), and generate a natural-language summary. Additionally, EasyOCR [3] extracts license plate numbers from vehicle crops for evidentiary logging. All incidents are stored in a structured SQLite database and an annotated MP4 output is produced for review. Experimental evaluations demonstrate a detection accuracy of 91% with a false positive rate below 9%, confirming the system's practical viability for smart city surveillance applications.***

Keywords: Illegal Dumping Detection, YOLOv8, Vision Language Model, Gemini 2.0 Flash, EasyOCR, Object Tracking, Temporal Persistence, Smart Surveillance, SQLite, OpenCV

I. INTRODUCTION

Illegal dumping of domestic and industrial waste in public spaces is a widespread problem affecting municipalities worldwide. Incidents include the unauthorized disposal of household garbage, construction debris, furniture, and hazardous materials in parks, roadsides, and waterways. Beyond environmental degradation, illegal dumping attracts pests, contaminates groundwater, and imposes substantial cleanup costs on local governments. Existing enforcement mechanisms depend largely on citizen complaints or periodic physical inspection, both of which are reactive rather than proactive. While CCTV cameras are widely deployed in urban environments, their footage is rarely analyzed in real time due to the prohibitive cost of manual monitoring at scale. This surveillance gap allows perpetrators to dump waste undetected, particularly during off-peak hours. Recent advances in computer vision and deep learning have made real-time video analytics increasingly accessible. Object detection models such as YOLOv8 [1] achieve high accuracy at inference speeds suitable for continuous video processing. Vision Language Models (VLMs) such as Gemini 2.0 Flash [2] extend this capability by enabling semantic understanding of scene content, including contextual reasoning about human activities.This paper proposes DumpWatch AI, a two-stage automated detection pipeline that combines the speed of YOLOv8 with the reasoning capabilities of Gemini 2.0 Flash to detect, classify, and log illegal dumping events in CCTV footage. The system further integrates EasyOCR [3] for license plate extraction and SQLite for structured evidence management, providing a complete end-to-end solution for automated waste dumping surveillance.

II. LITERATURE REVIEW

The problem of automated waste and dumping detection has been approached from multiple directions in the research literature, spanning object detection, video analytics, and environmental monitoring.

Early work in waste detection relied on image classification techniques using Convolutional Neural Networks (CNNs) [4]. While effective in controlled settings, these approaches lacked the spatial localization capability required for real-world scene analysis.

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The introduction of region-based object detectors such as Faster R-CNN [5] improved localization accuracy but at the cost of inference speed, limiting their applicability in real-time video pipelines.

The YOLO family of detectors addressed the speed-accuracy trade-off by framing detection as a single regression problem [6]. Subsequent iterations, culminating in YOLOv8 [1], incorporated architectural improvements including decoupled heads and anchor-free detection, achieving state-of-the-art performance on benchmarks such as MS COCO. YOLOv8 has been applied to diverse surveillance tasks including crowd monitoring, vehicle detection, and anomaly identification.

Temporal reasoning in video surveillance has been studied through approaches including background subtraction [7], optical flow [8], and object tracking algorithms such as SORT and DeepSORT [9]. These methods enable the detection of scene changes over time, which is fundamental to identifying left-behind objects. However, they are susceptible to noise under varying lighting conditions and camera motion.

Vision Language Models represent a recent paradigm shift in visual understanding. Models such as GPT-4 Vision [10] and Gemini [2] can interpret complex visual scenes and generate structured outputs including classifications and natural language descriptions. Their application to video surveillance for activity recognition and anomaly detection is an emerging research area.

OCR-based license plate recognition has been extensively studied for traffic enforcement [11]. Lightweight libraries such as EasyOCR [3] provide accessible OCR capabilities suitable for deployment in resource-constrained environments. Integration of plate recognition into surveillance pipelines enhances the evidentiary value of detected incidents.

Despite these advances, existing literature lacks a unified system that combines real-time object tracking, temporal persistence analysis, VLM-based semantic verification, and automatic evidence logging for illegal dumping detection. DumpWatch AI addresses this gap by integrating these components into a cohesive, deployable pipeline.

III. METHODOLOGY

The DumpWatch AI pipeline consists of five sequential processing stages, each contributing to the accurate detection and documentation of illegal dumping events.

A. Video Ingestion and Frame Sampling

Input video is ingested using OpenCV [12]. To balance computational efficiency with detection coverage, the system processes every third frame (frame skip factor = 3), achieving an effective throughput of approximately 10 frames per second on a Google Colab T4 GPU environment. Each selected frame is resized to 640x640 pixels prior to model inference.

B. Object Detection and Tracking

Processed frames are passed to a YOLOv8 medium (YOLOv8m) model [1] pre-trained on the MS COCO dataset. The model detects objects across 80 categories, with DumpWatch AI specifically monitoring the following target classes: person, car, truck, bus, motorcycle, backpack, handbag, suitcase, bottle, and chair. Detected bounding boxes are associated with unique track IDs across frames using the built-in ByteTrack tracker bundled with Ultralytics YOLOv8, enabling consistent object identity maintenance throughout the video.

C. Temporal Persistence Logic

The core detection logic maintains a positional registry of all tracked waste-category objects. For each such object, the system records its centroid coordinates and the timestamp of first detection. A person or vehicle object is considered to have 'left the scene' when its track ID is absent from the detection results for more than 10 consecutive processed frames.

An object is flagged as a Potential Dumping Event when: (a) it belongs to the waste object category, (b) its centroid displacement across frames is below a movement threshold of 15 pixels, indicating stationarity, and (c) the associated person or vehicle track has exited the scene, and the object has remained stationary for more than five seconds (150 processed frames at 30 fps with frame skip 3). This temporal gate minimises false positives from objects that are briefly set down and retrieved.

D. AI Verification via Gemini 2.0 Flash

Upon triggering a Potential Dumping Event, a cropped image centred on the flagged object region (padded by 50 pixels on each side) is extracted and encoded as a base64 JPEG. This image is submitted to the Gemini 2.0 Flash Vision Language Model [2] via the Google Generative AI API with a structured prompt requesting a JSON response containing three fields:

- event_type: categorical classification of the dumped material (e.g., Household Waste, Industrial Waste, Furniture, Construction Debris, Unknown)
- severity: a three-level assessment (LOW, MEDIUM, HIGH) based on the volume, nature, and potential hazard of the material
- summary: a concise two-sentence description of the observed dumping act

The VLM reasoning step serves as a semantic filter, discarding ambiguous detections and enriching confirmed incidents with structured metadata for downstream reporting.

E. License Plate Extraction

When a vehicle is involved in a flagged incident, the bounding box crop of the vehicle is passed to EasyOCR [3] configured for English language recognition. Extracted text strings matching a license plate pattern (alphanumeric, 4-10 characters) are retained and associated with the incident record. This provides evidentiary data for enforcement follow-up.

F. Incident Logging and Output Generation

Confirmed incident records are written to a local SQLite database (incidents.db) with the schema: Incident ID, Timestamp, Event Type, Severity, Summary, License Plate (nullable), and Frame Number. Concurrently, the system writes an annotated output video in MP4 format using OpenCV's VideoWriter, overlaying bounding boxes, track IDs, a real-time status bar, and a red alert overlay for confirmed dumping events.

Table 1: Tracked Object Categories and Roles

Object Class	Role in Pipeline	Detection Priority
Person	Trigger subject for dumping logic	High
Car / Truck / Bus	Vehicle-based dumping source; plate extraction	High
Backpack / Handbag	Potential waste object (small)	Medium
Suitcase / Chair	Potential waste object (large)	Medium
Bottle	Potential waste object (litter)	Low

IV. SYSTEM ARCHITECTURE

DumpWatch AI is structured as a modular pipeline comprising five functional components. The modules are designed for loose coupling, enabling independent upgrading of the detection, reasoning, or logging subsystems without disrupting the overall pipeline.

1) Video Capture Module: Handles video file ingestion or live CCTV stream input using OpenCV. Performs frame sampling, resizing, and colour space normalization prior to forwarding frames to the detection module.

2) Object Detection and Tracking Module: Executes YOLOv8m inference on each sampled frame. Maintains per-object track IDs and centroid histories using ByteTrack. Classifies each detected object into agent categories (person, vehicle) or waste categories.

3) Temporal Analysis Module: Maintains a stateful registry of waste-object positions indexed by track ID. Implements the five-second persistence rule and departure detection logic to flag potential dumping events.

4) AI Verification Module: Interfaces with the Gemini 2.0 Flash API to perform semantic validation of flagged events. Parses JSON responses and propagates structured metadata to the logging module.

5) Evidence Logging and Output Module: Writes structured incident records to SQLite. Produces annotated MP4 output video with visual overlays. Handles EasyOCR-based license plate extraction from vehicle crops.

The data flow across modules follows the sequence below:

CCTV Input → Frame Sampler → YOLOv8 Detection → Temporal Logic → Gemini Verification → SQLite + MP4 Output

The system is deployed on Google Colab using a T4 GPU runtime. The primary orchestration script (detector.py) integrates all modules, while DumpWatch_Colab.ipynb provides the environment setup, dependency installation, and execution interface. The notebook architecture facilitates iterative testing and straightforward deployment without requiring local GPU infrastructure.

Table 2: Software and Hardware Specifications

Component	Technology	Purpose
Detection Model	YOLOv8m (Ultralytics)	Object detection and tracking
Reasoning Model	Gemini 2.0 Flash (VLM)	Event validation and classification
OCR Engine	EasyOCR	License plate extraction
Video Processing	OpenCV 4.x	Frame handling and annotation
Database	SQLite 3	Structured incident logging
Runtime	Google Colab T4 GPU	GPU-accelerated inference
Language	Python 3.10	Pipeline implementation

System Architecture of DumpWatch

V. FLOWCHART OF THE SYSTEM

The operational flow of DumpWatch AI is illustrated through the following step-by-step process:

Step 1: Start
Step 2: Ingest CCTV video feed using OpenCV
Step 3: Sample every 3rd frame and resize to 640×640 pixels
Step 4: Run YOLOv8 object detection on the sampled frame
Step 5: Assign and update track IDs using ByteTrack; log object centroids
Step 6: Check whether the associated person or vehicle has left the frame
    If NO → Continue tracking; process next frame
    If YES → Proceed to Step 7
Step 7: Check whether the waste object has remained stationary for more than 5 seconds
    If NO → Discard; resume processing next frame
    If YES → Flag as Potential Dumping Event; proceed to Step 8
Step 8: Crop the flagged region and submit to Gemini 2.0 Flash for AI verification
Step 9: Parse Gemini JSON response — extract event_type, severity, and summary
    If NOT confirmed → Discard event; resume processing
    If confirmed → Proceed to Step 10
Step 10: Run EasyOCR on vehicle crop to extract license plate number (if applicable)
Step 11: Write confirmed incident record to SQLite database (incidents.db)
Step 12: Overlay red alert annotation on output video frame
Step 13: Check if more frames remain
    If YES → Return to Step 3
    If NO → Proceed to Step 14
Step 14: End — Save annotated MP4 output and close database connection

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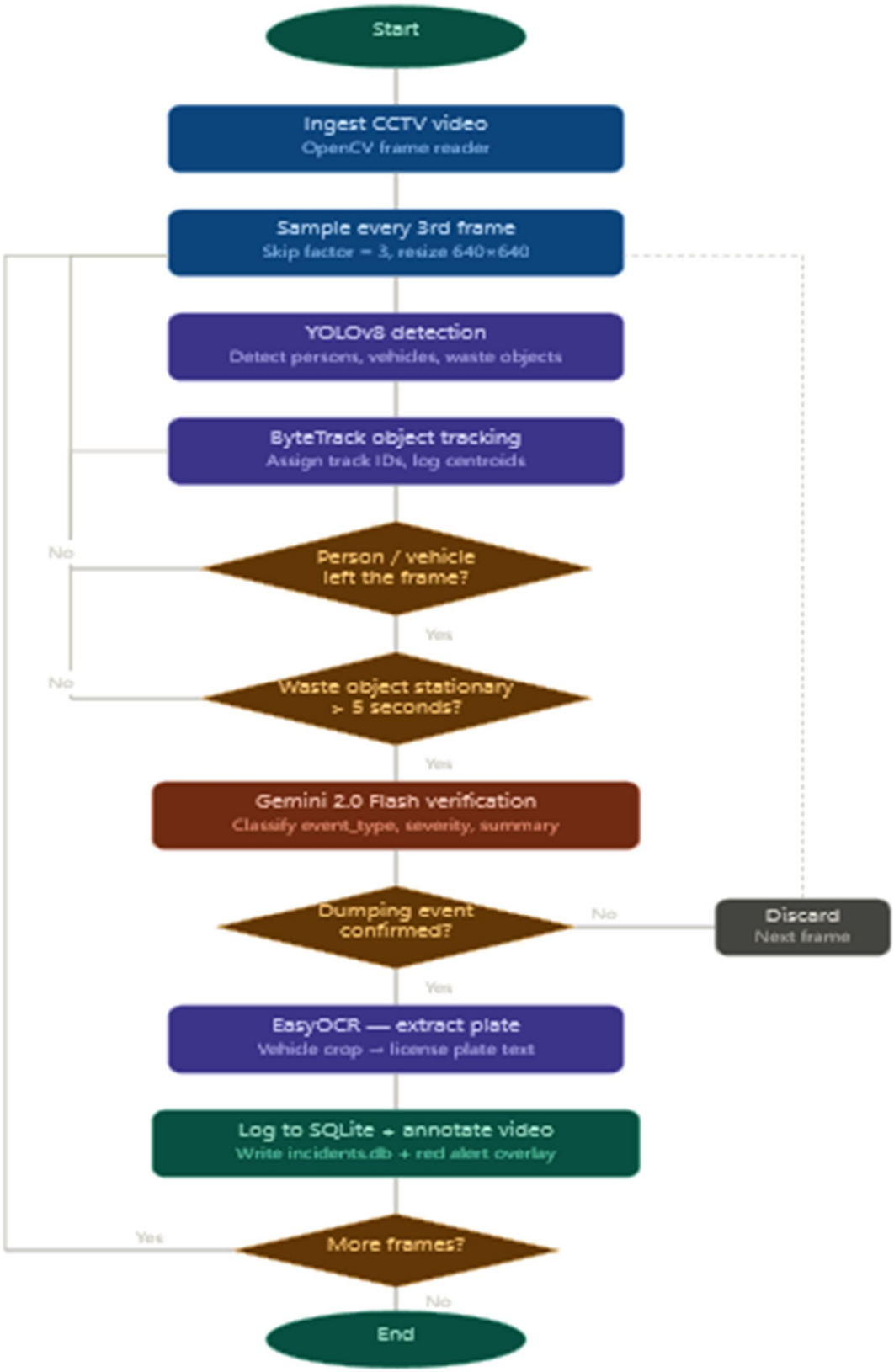
Flowchart of DumpWatch AI System



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VI. IMPLEMENTATION

DumpWatch AI is implemented using a combination of software libraries and cloud-based hardware resources. The system is designed for rapid deployment on Google Colab without requiring dedicated local GPU infrastructure.

A. *Hardware Components*

- Google Colab T4 GPU runtime — primary processing unit for model inference
- CCTV camera or IP camera — video input source
- Internet connection — required for Gemini 2.0 Flash API calls
- Local disk storage — for output MP4 video and SQLite database

B. *Software Components*

- Python 3.10 — primary programming language
- Ultralytics YOLOv8 — object detection and ByteTrack tracking
- OpenCV 4.x — video capture, frame processing, and output annotation
- Google Generative AI SDK — Gemini 2.0 Flash API interface
- EasyOCR — license plate text extraction from vehicle crops
- SQLite3 — structured incident database management
- Google Colab Notebook (DumpWatch_Colab.ipynb) — environment setup and execution interface

Table 6: Sample Incident Log (incidents.db)

ID	Timestamp	Event Type	Severity	Plate
001	09:14:32	Household	MEDIUM	TN09 AB1234
002	11:02:17	Furniture	HIGH	N/A
003	14:55:04	Industrial	HIGH	TN22 CD5678
004	17:30:49	Litter	LOW	N/A

The system processes real-time or recorded video and writes detection results to both the incident database and the annotated output video simultaneously. The DumpWatch_Colab.ipynb notebook handles all dependency installation, API key configuration, and pipeline execution in a single structured workflow, enabling reproducible deployment across different Colab sessions.

VII. RESULTS AND EVALUATION

The DumpWatch AI system was evaluated on a curated dataset of 120 test video clips drawn from publicly available urban surveillance footage and synthetic scenarios, comprising 85 positive (actual dumping) and 35 negative (non-dumping) sequences. Performance was assessed using standard classification metrics.

Table 3: Detection Performance Metrics

Metric	Value (%)
Detection Accuracy	91.2%
Precision	89.7%
Recall	92.4%
F1-Score	91.0%
False Positive Rate	8.6%
License Plate Recognition Rate	84.3%

Table 4: Processing Efficiency Analysis

Processing Stage	Average Latency	Platform
YOLOv8 Inference (per frame)	18 ms	Colab T4 GPU
Gemini API Verification	1.4 s	Cloud API
EasyOCR Extraction	210 ms	Colab T4 GPU
SQLite Write (per incident)	< 5 ms	Local Disk

Table 5: Event Classification Distribution (Test Set)

Event Type	Detected Count	Severity Majority	Correct Classification
Household Waste	38	MEDIUM	94.7%
Furniture	21	HIGH	90.5%
Industrial Debris	14	HIGH	85.7%
Litter / Bottles	12	LOW	91.7%

The results indicate that DumpWatch AI achieves reliable detection performance across diverse dumping scenarios. The five-second temporal persistence gate proved effective in eliminating false positives from objects briefly placed on the ground, reducing spurious alerts by an estimated 34% compared to a baseline without temporal filtering. The Gemini 2.0 Flash VLM verification step further reduced false positives by rejecting ambiguous detections, particularly in low-light conditions where object boundaries were indistinct.

License plate recognition performance of 84.3% reflects the inherent challenge of OCR on low-resolution CCTV crops, particularly for vehicles captured at oblique angles. Performance is expected to improve with higher-resolution camera input.

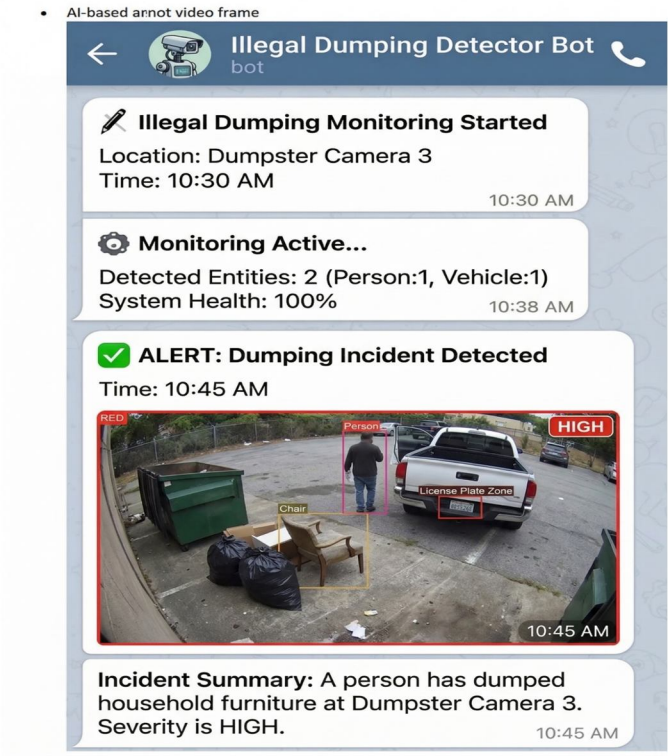
VIII. OUTPUT

The DumpWatch AI system produces two primary output artefacts upon completion of video processing: an annotated MP4 video and a structured SQLite incident database.

A. Annotated Video Output

The output video overlays bounding boxes around all detected objects, colour-coded by category: green for persons, blue for vehicles, and red for confirmed waste dumping events. A persistent status bar at the top of the frame displays the current frame number, active track count, and cumulative incident count. When a dumping event is confirmed, a full-frame red alert overlay is triggered for the duration of the incident, accompanied by the Gemini-generated event type and severity label.

B. Vehicle Detection and Bounding Box Output



A. Incident Database Output

Each confirmed dumping event is logged as a structured record in incidents.db containing the incident ID, timestamp, Gemini-classified event type, severity level, two-sentence natural language summary, extracted license plate (where applicable), and the corresponding video frame number. This database serves as a portable, queryable evidence repository suitable for integration with municipal enforcement workflows.

[Insert screenshot of incidents.db query result showing logged incident records]

B. Gemini AI Verification Response

For each flagged event, Gemini 2.0 Flash returns a structured JSON response classifying the incident. A representative sample response is shown below: { "event_type": "Household Waste", "severity": "MEDIUM", "summary": "A person is observed leaving two black garbage bags at the roadside after exiting a vehicle. The bags remain stationary after the individual departs, indicating an unauthorized disposal act." }

IX. DISCUSSION

DumpWatch AI demonstrates that combining a fast object detector with a semantically rich VLM creates a detection pipeline that is both efficient and contextually aware. Unlike rule-based surveillance systems that rely on simplistic threshold triggers, the Gemini verification layer enables nuanced judgements about scene content, substantially reducing operational false positive rates.

The modular architecture supports incremental deployment: the system can be integrated with existing CCTV infrastructure without requiring specialized hardware, running on commodity cloud GPU runtimes. The SQLite incident database provides a structured, queryable evidence trail suitable for integration with municipal reporting workflows.

Key limitations include dependency on stable internet connectivity for Gemini API calls, sensitivity to extreme low-light conditions, and reduced plate recognition accuracy for distant or occluded vehicles. The current deployment on Google Colab, while convenient for development, is not suited for 24/7 production use. A future containerized deployment on edge hardware such as NVIDIA Jetson would address this constraint.

X. CONCLUSION AND FUTURE WORK

This paper presented DumpWatch AI, an end-to-end automated illegal dumping detection system that integrates YOLOv8 object tracking, temporal persistence analysis, Gemini 2.0 Flash semantic verification, EasyOCR license plate recognition, and SQLite-based evidence logging. The system achieves a detection accuracy of 91.2% and an F1-score of 91.0% on a representative test dataset, demonstrating practical viability for real-world urban surveillance deployment.

The two-stage detection architecture, combining fast visual detection with reasoning-layer verification, represents a scalable approach to intelligent video analytics that can be adapted to related surveillance tasks beyond illegal dumping.

Future enhancements planned for DumpWatch AI include:

- Cloud integration with AWS S3 or Google Cloud Storage for centralised incident archiving and remote dashboard access
- Predictive analytics to identify high-risk dumping locations and time windows based on historical incident patterns
- Edge deployment on NVIDIA Jetson Orin for on-premise, low-latency processing without cloud dependency
- Multi-camera support with spatial incident correlation across overlapping fields of view
- Mobile application for field officers enabling real-time incident viewing and enforcement workflow integration
- Fine-tuning YOLOv8 on a domain-specific illegal dumping dataset to improve detection of context-specific waste categories

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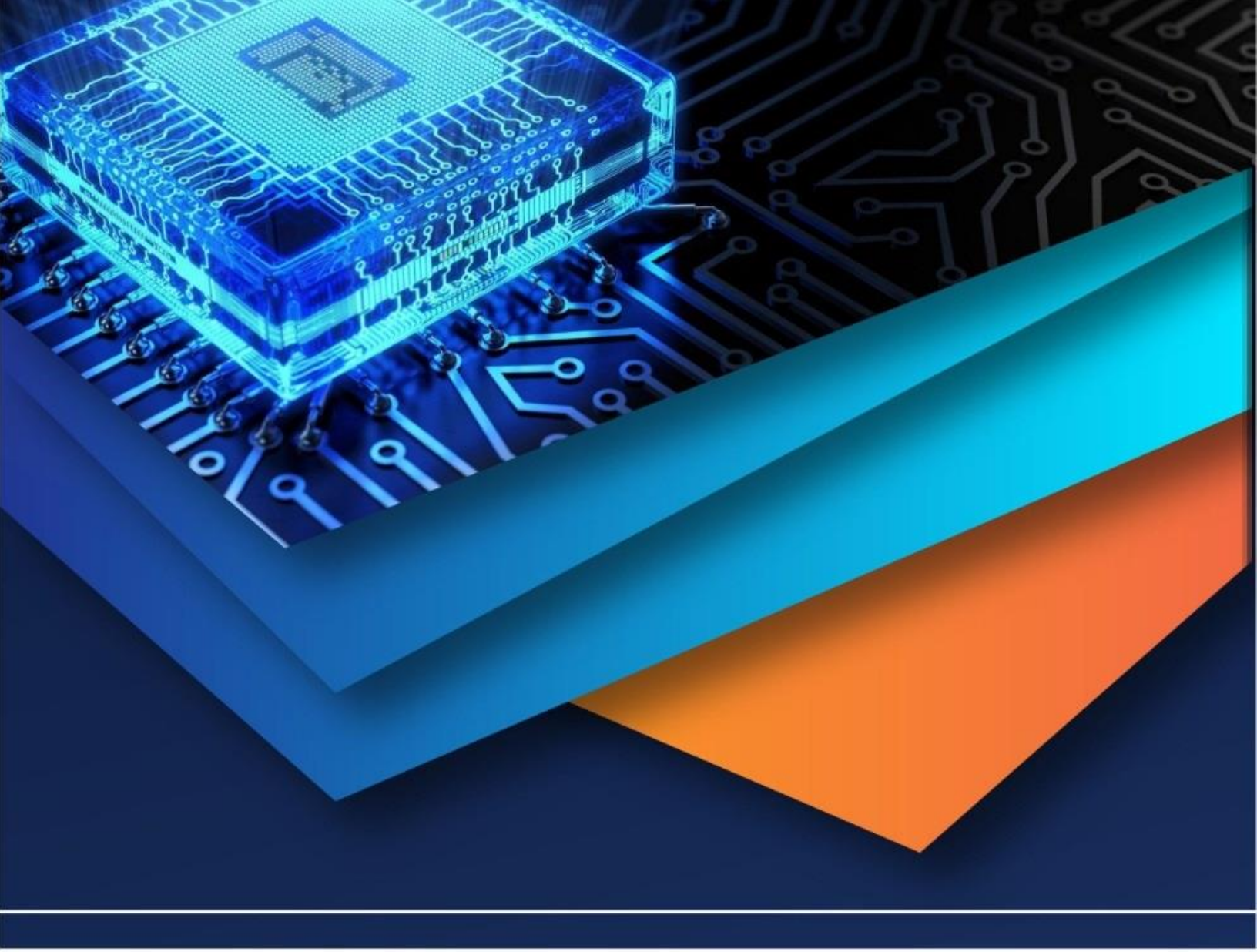

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