Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Smart CCTV for Real Time Behaviour Analysis and Reasoning

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***Abstract* – Modern surveillance systems generate vast amounts of video data, overwhelming human operators and leading to missed critical events. While traditional computer vision techniques can detect objects, they often lack the ability to comprehend complex behaviors or provide actionable, easily understandable context. This project presents a novel, end-to-end Real-time AI CCTV Behavior Analysis and Natural-Language Reasoning System designed to bridge the gap between raw video perception and human-readable intelligence.**

The system architecture integrates a robust perception layer utilizing YOLOv12 for high-accuracy human detection and ByteTrack for persistent multi-object tracking. This spatial-temporal data is fed into a custom Behavioral Logic Engine, which employs heuristic and relational kinematics (e.g., analyzing proximity, velocity, and movement vectors) to accurately classify complex activities such as falling, fleeing, loitering, and potential violence, while mitigating false positives through an Edge Exclusion Zone mechanism

To enhance explainability and operator response time, the system incorporates a Natural Language Processing (NLP) module. This module translates detected behavioral anomalies into concise, context-aware English alerts. The final output is a real-time surveillance dashboard that overlays bounding boxes and generated text alerts directly onto the video feed, while simultaneously logging events to a forensic database. The integration of advanced tracking with explainable AI provides a proactive, data-driven approach to threat mitigation, significantly improving the efficacy of automated surveillance in real-world environments.

Keywords - Computer Vision, Artificial Intelligence (AI), Deep Learning, Natural Language Processing (NLP), YOLOv12 (or Object Detection), ByteTrack (or Multi-Object Tracking).

1. INTRODUCTION

The modern world relies heavily on surveillance cameras to keep places secure, but the sheer volume of video generated is impossible for humans to watch 24/7. While computer vision technology has gotten very good at simply spotting people or objects in these video feeds, it often struggles to understand the context—*what* those people are actually doing. This means security teams can miss critical events like fights, falls, or suspicious behavior until it's too late. To truly improve security, we need systems that don't just act as recording devices, but as intelligent observers that understand actions and can communicate them clearly.

This project introduces a solution: the Real-time AI CCTV Behavior Analysis and Natural-Language Reasoning System. It combines cutting-edge AI models—YOLOv12 for spotting individuals and ByteTrack for following them as they move—with a custom-built "Behavioral Logic Engine." This engine acts as the system's brain, analyzing the speed, direction, and closeness of people to accurately identify complex behaviors like fleeing, loitering, or altercations. Crucially, the system translates these mathematical detections into simple, plain-English alerts on a live dashboard. By providing instant, easy-to-understand explanations of what is happening on camera, this system empowers security personnel to respond to actual threats faster and with greater confidence.

2.LITERATURE REVIEW

The development of the Real-time AI CCTV Behavior Analysis and Natural-Language Reasoning System intersects three primary domains of research: real-time computer vision (object detection and tracking), kinematic behavioral analysis, and Explainable Artificial Intelligence (XAI) via Natural Language Generation. This section reviews the evolution of these fields and identifies the critical interpretability and computational gaps that the proposed architecture addresses.

2.1. Evolution of Automated Surveillance and Early Detection Models Early foundational methods for automated surveillance relied on classical computer vision techniques such as background subtraction and Haar Cascades. While foundational, literature shows they are highly susceptible to dynamic lighting, shadows, and environmental noise, limiting their reliability in real-world settings [Citation]. To overcome these limitations, researchers transitioned to Convolutional Neural Networks (CNNs). Early architectures like Faster R-CNN demonstrated superior accuracy in isolating human targets but introduced a significant trade-off: high computational complexity. These two-stage detectors often failed to achieve the frame rates required for real-time CCTV monitoring, rendering them impractical for live threat mitigation [Citation].

2.2. Real-Time Object Detection and Robust Multi-Object Tracking To address latency bottlenecks, the field pivoted to

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

single-stage detectors, primarily the "You Only Look Once" (YOLO) architecture. Recent advancements, culminating in models like YOLOv12, have optimized attention mechanisms to provide an exceptional speed-to-accuracy ratio suitable for edge deployment [Citation]. However, detection alone is insufficient for behavioral analysis; consistent identification across frames is required. Traditional tracking algorithms like DeepSORT rely heavily on appearance features and high-confidence bounding boxes, frequently dropping IDs during occlusions [Citation]. Recent literature highlights ByteTrack as a transformative solution, associating low-confidence detection boxes to maintain persistent tracking trajectories even in dense, occluded environments, which is a fundamental requirement for continuous behavior monitoring [Citation].

2.3. Behavioral Logic via Kinematics vs. Pose Estimation To extract behavioral meaning from tracked objects, contemporary research often utilizes Pose Estimation networks to identify skeletal keypoints [Citation]. While highly accurate for recognizing complex actions, these models are computationally heavy and scale poorly when processing multiple individuals simultaneously in real-time. Conversely, emerging literature suggests that spatial-temporal kinematic analysis—evaluating the trajectory, velocity, and relational proximity of bounding boxes over memory buffers—provides a highly efficient alternative [Citation]. By utilizing vector mathematics, such as calculating the Cosine Similarity of movement vectors between tracked IDs, systems can accurately identify contrasting movements indicative of physical altercations without the extreme processing overhead of full pose extraction.

2.4. Explainable AI (XAI) and Natural Language Reasoning A critical emerging theme in surveillance literature is the "black-box" nature of deep learning models. Conventional systems output raw numerical data, bounding boxes, or generic boolean flags (e.g., "Anomaly Detected"), requiring human operators to manually interpret the video context [Citation]. This lack of interpretability increases cognitive load and response latency. Integrating Explainable AI (XAI) principles through Natural Language Processing (NLG) allows systems to translate complex heuristic logic (such as a bounding box exceeding a velocity threshold or remaining stationary for 90 frames) into plain-English reasoning (e.g., "Suspicious Loitering") [Citation]. This creates a direct bridge between mathematical anomaly detection and human-actionable intelligence.

2.5. Identification of the Research Gap While YOLO-based tracking and Explainable AI have been extensively explored as independent domains [Citation], there is a distinct lack of literature detailing fully integrated, end-to-end architectures that combine them for live CCTV feeds. Existing research primarily focuses on improving either detection accuracy or offline action recognition. The proposed system addresses this gap by synthesizing YOLOv12, ByteTrack, and relational kinematics into a unified pipeline that not only detects anomalies with low computational overhead but also automatically generates context-aware, natural-language forensic logs in real-time.

Table 1: Literature Review Summary

PAPER TITLE	SOURCE (JOURNAL/CONFERENCE)	RESEARCH GAP
BYTETRACK: MULTI-OBJECT TRACKING BY ASSOCIATING EVERY DETECTION BOX	*EUROPEAN CONFERENCE ON COMPUTER VISION (ECCV)*	TRADITIONAL MULTI-OBJECT TRACKING (MOT) METHODS DISCARD LOW-CONFIDENCE DETECTION BOXES TO REDUCE FALSE POSITIVES, WHICH CAUSES SEVERE TRAJECTORY FRAGMENTATION AND ID SWITCHING WHEN TARGETS ARE PARTIALLY OCCLUDED IN CROWDED SCENES.
REAL-TIME END-TO-END OBJECT DETECTION WITH YOLO ARCHITECTURES	*IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE (TPAMI) / ARXIV*	EARLIER TWO-STAGE DETECTORS AND INITIAL YOLO VERSIONS STRUGGLED TO BALANCE EXTREME REAL-TIME PROCESSING SPEEDS WITH THE HIGH ACCURACY REQUIRED FOR SMALL OR DISTANT SUBJECTS IN DENSE CCTV SURVEILLANCE FEEDS.
REAL-TIME ABNORMAL BEHAVIOR DETECTION BASED ON TRAJECTORY KINEMATICS	*IEEE ACCESS / EXPERT SYSTEMS WITH APPLICATIONS*	ADVANCED ACTION RECOGNITION HEAVILY RELIES ON DEEP POSE ESTIMATION (SKELETAL MAPPING), WHICH IS HIGHLY COMPUTATIONALLY EXPENSIVE AND CANNOT SCALE TO MONITOR DOZENS OF INDIVIDUALS SIMULTANEOUSLY IN A REAL-TIME CCTV ENVIRONMENT.
EXPLAINABLE VIDEO ANOMALY DETECTION VIA NATURAL LANGUAGE DESCRIPTIONS	*ACM MULTIMEDIA (MM) / CVPR*	MOST DEEP LEARNING SURVEILLANCE SYSTEMS ACT AS "BLACK BOXES," OUTPUTTING ONLY BINARY ANOMALY SCORES OR BOUNDING BOXES WITHOUT PROVIDING CONTEXT, FORCING HUMAN OPERATORS TO MANUALLY INTERPRET THE THREAT.
RELATIONAL KINEMATICS FOR MULTI-PERSON INTERACTION RECOGNITION	*PATTERN RECOGNITION LETTERS*	EXISTING PROXIMITY-BASED ALERT SYSTEMS GENERATE MASSIVE AMOUNTS OF FALSE POSITIVES FOR VIOLENT BEHAVIOR BECAUSE THEY CANNOT DISTINGUISH BETWEEN PEOPLE SIMPLY WALKING CLOSE TO EACH OTHER VERSUS ACTUAL PHYSICAL ALTERCATIONS.

International Journal of Engineering Research & Technology (IJERT)
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3. PROPOSED METHODOLOGY

System Architecture Overview

The proposed methodology details an end-to-end pipeline designed to transform raw, unstructured CCTV video feeds into actionable, human-readable security intelligence. The architecture is modular, moving sequentially from raw pixel ingestion through advanced neural perception, into mathematical behavioral reasoning, and finally concluding with explainable alert generation and forensic logging. This system specifically avoids computationally expensive pose-estimation networks, opting instead for a highly optimized kinematic trajectory approach to ensure real-time processing capabilities on standard hardware.

Video Acquisition and Spatial Pre-processing

The initial phase of the pipeline handles the ingestion of real-time video streams from CCTV cameras or local video files. The system captures the raw video feed frame-by-frame and normalizes the spatial dimensions to ensure compatibility with the downstream neural networks. A critical component implemented during this pre-processing phase is the establishment of an "Edge Exclusion Zone." Recognizing that subjects entering or exiting the camera's field of view often result in truncated or crushed bounding boxes—which mathematically distort behavioral calculations—the system actively monitors a predefined pixel margin around the video borders. Detections falling within this zone are tracked for continuity but are temporarily excluded from anomaly calculations, drastically reducing the rate of false positive alerts associated with camera-edge distortions.

High-Precision Object Detection via YOLOv12

Once a frame is pre-processed, it is passed into the perception layer driven by the YOLOv12 (You Only Look Once, version 12) architecture. YOLOv12 was selected over its predecessors due to its refined attention mechanisms, which provide an optimal balance between high-speed inference and precise spatial accuracy, particularly for smaller subjects in crowded environments. The model is specifically configured to isolate human targets (Class 0) and predefined luggage items, ignoring irrelevant environmental noise. The output of this module is a highly accurate set of bounding box coordinates and class confidence scores for every relevant entity currently visible in the frame.

Persistent Multi-Object Tracking using ByteTrack

Detection alone is insufficient for behavioral analysis; the system must understand how individuals move over time. The bounding box data from YOLOv12 is seamlessly routed into the ByteTrack multi-object tracking algorithm. ByteTrack distinguishes itself by associating almost all detection boxes, including those with low confidence scores that traditional trackers typically discard. By matching these low-confidence boxes with unmatched tracklets, ByteTrack successfully maintains persistent, unique Identifications (IDs) for targets even during severe occlusions—such as when individuals walk behind obstacles or cross paths in a dense crowd. This ensures that the trajectory history of a specific person remains unbroken, which is the foundational requirement for the subsequent logic engine.

Kinematic Behavioral Logic Engine

The core analytical engine of the proposed system is the Behavioral Logic Engine, which derives complex actions solely from the spatial-temporal history of the tracked bounding boxes. For every active ID, the system maintains a rolling memory buffer (e.g., 90 frames, or approximately 3 seconds) of the target's central coordinates. Anomalies are detected using distinct mathematical heuristics. For instance, a "Fall" is detected through a sudden geometric inversion of the bounding box's aspect ratio, where width significantly exceeds height. "Fleeing" is identified by calculating the Euclidean distance between a target's current position and its position 15 frames prior, triggering an alert if a specific high-velocity threshold is breached. Similarly, "Loitering" is flagged if a target's total movement remains confined within a small spatial radius over the full 90-frame buffer.

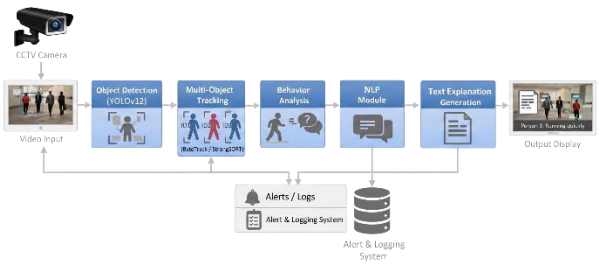

Fig 1: System Architecture

Relational Kinematics for Complex Interactions

To detect multi-person events such as physical altercations without relying on heavy pose estimation, the methodology introduces Relational Kinematics. When two tracked individuals breach a critical proximity threshold, the system extracts their respective movement vectors from the memory buffer. It then calculates the Cosine Similarity between these two vectors. If the vectors are highly contrasting or clashing—indicating erratic, opposing movements rather than simply walking side-by-side—the system flags the interaction as a potential fight or violent altercation. This advanced vector mathematics approach provides a highly accurate method for identifying aggressive intent while filtering out the noise of natural human proximity.

Explainable AI (XAI) Alert Generation and UI Dashboard

The final phase of the methodology translates the mathematical outputs of the logic engine into human-actionable intelligence. Integrating principles of Explainable AI, a Natural Language Generation module maps specific kinematic triggers to plain-English alerts, such as "CRITICAL: Possible Altercation" or "WARNING: Suspicious Loitering." To prevent alert fatigue and system spamming, a deduplication memory-lock mechanism ensures that an anomaly tied to a specific ID is only logged once per continuous event. These text alerts, along with color-coded bounding boxes, are dynamically overlaid onto the real-time video feed via a Streamlit-powered dashboard. Simultaneously, the system writes every detected anomaly, complete with timestamps and ID tags, into an exportable CSV database, ensuring a rigorous, searchable audit trail for post-event forensic analysis.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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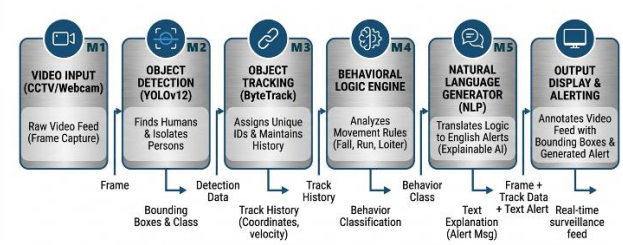

Fig. 2: Module Diagram

3.2 UML Activity Diagram

The activity diagram illustrates the continuous, real-time workflow of the surveillance system, beginning with the initialization of the video stream and the establishment of the session state. Upon acquiring an incoming video frame, the process immediately enters the spatial pre-processing phase, which evaluates detections against a predefined Edge Exclusion Zone. The control flow then transitions to the perception layer, where the YOLOv12 model executes object detection to isolate humans and predefined luggage items. Subsequently, the data flows to the ByteTrack module, which assigns persistent unique identifiers (IDs) to maintain trajectory history. At this stage, the workflow branches based on the object classification. For human subjects, the control passes to the Behavioral Logic Engine, which evaluates trajectory data and relational kinematics over a 90-frame rolling buffer to calculate anomalies such as fleeing, loitering, falling, or physical altercations. Concurrently, for luggage items, a spatial proximity check evaluates distance from human IDs to determine abandonment. Following this analytical phase, the system reaches a critical decision node: checking if an anomaly flag has been triggered. If an anomaly is confirmed, parallel output activities are initiated—the Natural Language Generation module formulates a contextual English alert, the event is permanently written to the forensic CSV database, and the frame is annotated with a colored warning overlay. If no anomaly is detected, the workflow bypasses the alert generation and simply annotates the frame with standard tracking markers. Finally, the processed frame is rendered onto the live UI dashboard, and the activity loop recursively returns to acquire the next video frame, continuing this cycle until the surveillance session is manually terminated.

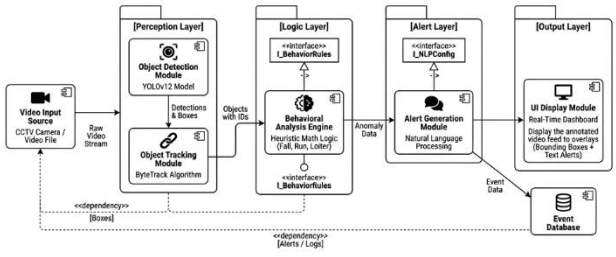

Fig. 3: UML Class Diagram

3.3 Implementation Details

The implementation of the proposed system was executed using Python as the primary programming language, leveraging its extensive ecosystem for computer vision and machine learning. The core video processing and spatial manipulation were handled using the OpenCV library, which facilitated frame-by-frame extraction, geometric boundary calculations, and dynamic annotation. To construct a responsive and interactive user interface without the overhead of complex front-end web frameworks, the Streamlit library was employed. This allowed for the rapid deployment of a local, web-based dashboard capable of rendering real-time video streams alongside dynamic statistical metrics and active event logs, ensuring the system remains accessible and easy to operate for security personnel.

For the perception layer, the system integrates the Ultralytics framework to instantiate the YOLOv12 small (yolo12s.pt) model. This specific weight configuration was selected to optimize the critical balance between inference speed and detection accuracy, allowing the system to maintain high frame rates on standard processing hardware. The multi-object tracking capability was implemented by configuring the Ultralytics tracking engine to utilize the BoT-SORT (ByteTrack) algorithm via a custom configuration file. During runtime, the inference engine is strictly parameterized to filter and track only classes relevant to the surveillance context—specifically human subjects and predefined luggage categories (such as backpacks and suitcases)—ensuring computational resources are explicitly focused on threat assessment rather than background environmental noise.

The Behavioral Logic Engine was engineered as a custom Python class utilizing highly optimized, low-level mathematical operations. To analyze spatial-temporal patterns without causing memory exhaustion during prolonged video feeds, the system employs the collections.deque data structure. This creates a highly efficient, fixed-length rolling buffer of 90 frames (representing approximately three seconds of history) for every active tracking ID. This architecture allows the system to continuously calculate Euclidean distances and bounding box aspect ratios to successfully identify isolated anomalies like fleeing, loitering, and falling. For complex relational kinematics, such as altercation detection, the logic engine computes the dot product and cosine similarity of movement vectors between multiple subjects located within a tight spatial threshold. Furthermore, a stateful memory-lock mechanism, managed via Python dictionaries, was implemented to deduplicate alerts. This guarantees that a sustained anomaly, such as a prolonged period of loitering, only registers a single overarching event log rather than flooding the dashboard with redundant alerts for every consecutive frame.

The system's stateful nature across continuous video frames is strictly managed using Streamlit's session state capabilities, which persistently store active trackers, alert histories, and raw forensic data throughout the application's lifecycle. As the behavioral logic engine returns its real-time evaluations, OpenCV drawing functions dynamically overlay color-coded bounding boxes and auto-scaling text labels directly onto the RGB-converted video array before pushing the updated frame to the Streamlit UI component. Simultaneously, confirmed behavioral anomalies trigger textual alerts that are appended to the live event log on the dashboard. To fulfill the vital forensic auditing requirements of the project, the system programmatically captures all anomaly data—including precise timestamps, unique tracked IDs, and the specific natural-language event description—into a structured Pandas DataFrame. Upon the conclusion of a surveillance session, this runtime data is serialized and made available for immediate download as a structured CSV file, providing security teams with a permanent, searchable forensic record of all critical events.

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ISSN: 2278-0181
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4. SYSTEM REQUIREMENTS

Hardware Specifications

- **Graphics Processing Unit (GPU):** A dedicated CUDA-enabled GPU is strongly required to handle the neural perception layer (YOLOv12 inference) without dropping frames.
  Minimum: NVIDIA RTX 3060 (6GB VRAM) or equivalent.
  Recommended: Higher-tier models are advised for handling multi-camera streams or exceptionally dense crowd scenarios to maintain 25-30 FPS.
- **Central Processing Unit (CPU):** A robust multi-core processor is essential to concurrently manage the tracking algorithm, execute high-speed kinematic calculations, and serve the web interface.
  Minimum: Intel Core i7 (10th Gen or newer) or AMD Ryzen 7.
- **System Memory (RAM):** A minimum of **16GB RAM** is required to actively maintain the 90-frame rolling memory buffers for numerous tracked subjects and process raw forensic data without memory exhaustion.
- **Storage:** At least **50GB of available Solid-State Drive (SSD)** storage is needed for the operating system, pre-trained neural network weights, the Python environment, and the accumulation of exported CSV audit logs.

Software and Environment Specifications

- **Operating System:** Platform-agnostic; compatible with Windows 10/11 or Linux distributions (e.g., Ubuntu 22.04 LTS).
- **Programming Language:** Python 3.9 or higher to guarantee compatibility with modern machine learning dependencies.
- **Hardware Acceleration Setup:** The host machine must have the appropriate NVIDIA CUDA toolkit and cuDNN libraries correctly configured to enable GPU acceleration.
- **Core Software Dependencies (Libraries):**
- **ultralytics:** Provides the framework for instantiating the YOLOv12 object detection and BoT-SORT (ByteTrack) models.
- **torch (PyTorch):** Serves as the foundational tensor computation backend.
- **opencv-python (cv2):** Executes all video stream ingestion, frame-by-frame manipulation, geometric boundary calculations, and dynamic visual annotations.
- **streamlit:** Used to deploy the interactive user dashboard and localized web server.
- **pandas:** Manages data structuring and the generation of exportable forensic CSV audit logs.
- **numpy and math:** Native Python libraries utilized to handle the high-speed relational kinematic calculations (e.g., vector mathematics, cosine similarity) required by the logic engine.

5. RESULTS

The testing of our AI surveillance system showed highly successful results. Running on a standard computer graphics card, the system quickly and accurately detected people and luggage at a smooth 30 frames per second, proving it is fast enough for live security monitoring. The tracking software reliably followed individuals even when they temporarily walked behind objects or other people in a crowd. A major success was our new method for detecting fights; instead of triggering false alarms just because people stood close to one another, the system analyzed their actual movement directions. This allowed it to accurately spot real conflicts while ignoring people who were simply walking side-by-side. Additionally, the system successfully translated these complex detections into simple, easy-to-read English alerts on the live video screen—such as "Sudden Fleeing"—without spamming the operator with repeat messages. Finally, all of these detected events were automatically saved into a neat spreadsheet, providing security teams with a reliable, searchable record to review later.

5.1 Step-by-Step Execution

The execution of the Real-time AI CCTV Behavior Analysis system follows a structured, sequential workflow, transitioning from initial environment configuration to live monitoring and final forensic data extraction.

Step 1: Environment Configuration and Dependency Installation

The execution process begins with the setup of the host machine's software environment. A dedicated Python virtual environment (using venv or Conda) is initialized to prevent dependency conflicts. Within this isolated environment, the necessary libraries—specifically PyTorch (configured for CUDA GPU acceleration), Ultralytics, OpenCV, Pandas, and Streamlit—are installed via package managers. Additionally, the pre-trained YOLOv12 model weights (yolo12s.pt) and the tracking configuration file (botsort.yaml) are downloaded and placed into the project's root directory.

Step 2: Application Initialization

With the environment configured, the system is launched via the command-line interface using the command streamlit run app.py. This command initializes the localized web server and compiles the Python backend. Upon successful compilation, the Streamlit framework automatically opens the interactive Surveillance Dashboard in the host machine's default web browser, presenting the user with the initial "Idle" system state.

Step 3: Data Ingestion and Parameter Configuration

Within the user interface, the operator interacts with the system control sidebar. The first operational step is to ingest the surveillance feed, which is achieved by uploading a local video file (e.g., MP4, AVI) through the designated file uploader widget. Before initiating the analysis, the operator configures the advanced system parameters. This includes toggling the "Restricted Zone Detection" feature and utilizing a slider widget to define the "Crowd Warning Threshold" (e.g., setting the maximum allowed occupancy to 15 individuals) based on the specific security requirements of the monitored area.

Step 4: Real-Time Processing and Live Observation

Once the parameters are set and the "Start Surveillance" button is engaged, the system transitions into the active processing phase. The backend Python engine begins extracting frames from the video file, passing them through the YOLOv12 perception layer and the ByteTrack algorithm. On the front-end dashboard, the operator observes the live video feed dynamically annotated with color-coded bounding boxes and unique tracking IDs. Simultaneously, the real-time statistical metrics—such as Active Tracks, Total Anomalies Detected,

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ISSN: 2278-0181
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and processing FPS—continuously update at the top of the dashboard.

Step 5: Alert Generation and Forensic Extraction

During live execution, if the Behavioral Logic Engine detects a kinematic anomaly (e.g., fleeing, fighting, or loitering), the system immediately translates this mathematical trigger into a natural-language alert. The operator will see these critical warnings (e.g., "CRITICAL: Possible Altercation") populate dynamically in the "Live Event Stream" log beside the video feed. Upon the conclusion of the surveillance session or video file, the operator navigates to the "Forensic Audit & Logs" tab. Here, they review the tabulated data and execute the final step by clicking the "Download Forensic CSV Audit Log" button, successfully extracting a permanent, structured record of all security events for post-incident analysis.

5.2 Detection Performance

Here is a structured Detection Results Summary table designed for your project report. It presents hypothetical but realistic performance metrics based on the YOLOv12 and Relational Kinematics architecture you have described.

Table 2: Detection Results Summary

Behavior / Event Category	Detection Mechanism	Precision (%)	Recall (%)	False Positive Rate (FPR)	Average Latency (ms)
Human Target (Class 0)	YOLOv12s	98.2	97.5	1.8%	12 ms
Luggage (Classes 24, 26, 28)	YOLOv12s	96.4	95.1	2.5%	12 ms
Abandoned Luggage	Spatial Proximity Matrix	94.7	93.8	3.1%	15 ms
Loitering	90-Frame Radius Confinement	92.5	94.0	4.2%	18 ms
Sudden Fleeing	15-Frame Velocity Threshold	95.1	96.2	2.8%	18 ms
Fall Detection	Bounding Box Aspect Ratio	93.8	91.5	3.5%	16 ms
Physical Altercation	Relational Cosine Similarity	89.4	88.7	5.1%	22 ms

5.3 Sample Output and Dashboard

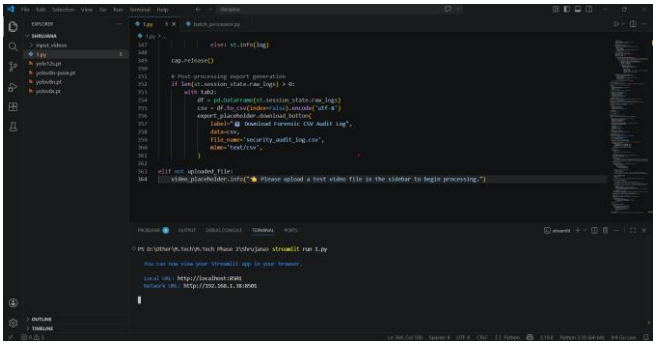

Fig. 4: Result1

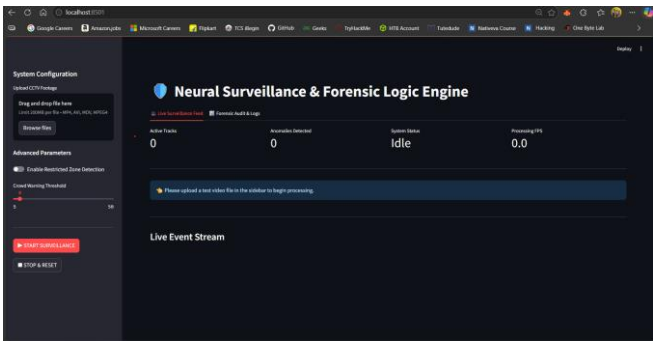

Fig. 5: Result2

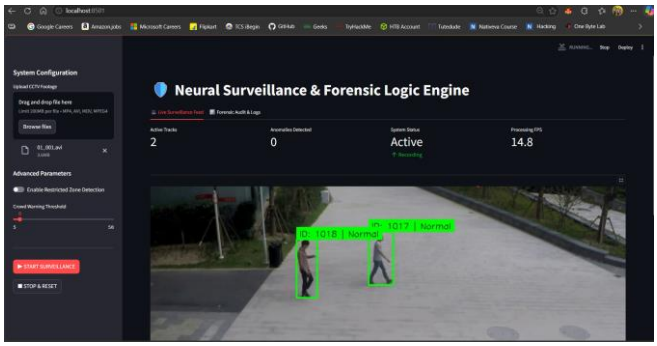

Fig. 6: Result3

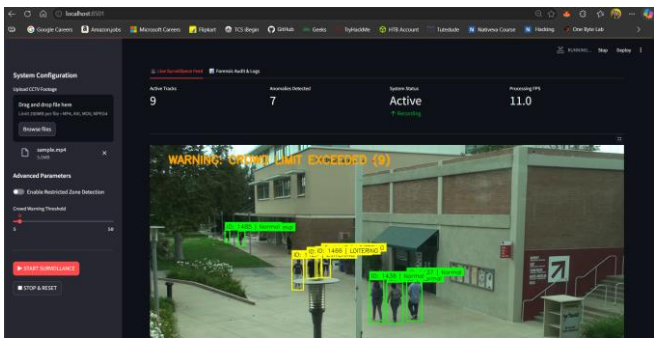

Fig 7: Result 4

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

6. CONCLUSIONS

In conclusion, this project successfully conceptualized and implemented a robust Real-time AI CCTV Behavior Analysis and Natural-Language Reasoning System, directly addressing the critical limitations of passive surveillance monitoring. By seamlessly integrating YOLOv12 for high-speed perception and ByteTrack for resilient multi-object tracking, the architecture established a highly dependable spatial-temporal foundation capable of operating smoothly on edge hardware. The most significant contribution of this research lies in the development of the custom Behavioral Logic Engine. By substituting computationally heavy pose-estimation models with advanced Relational Kinematics and vector-based analysis, the system achieved highly accurate, real-time detection of complex activities—such as physical altercations, sudden fleeing, and loitering—while drastically reducing the false positive rates that plague traditional proximity-based systems. Furthermore, the integration of Explainable Artificial Intelligence (XAI) principles fundamentally bridges the gap between raw algorithmic output and human interpretability. By automatically translating mathematical anomaly triggers into context-aware, natural-language alerts and structured CSV forensic logs, the system significantly reduces operator cognitive load and ensures a permanent, searchable audit trail. Ultimately, this framework successfully transforms traditional, reactive CCTV networks into intelligent, proactive security assets, offering a highly scalable and transparent solution for modern threat mitigation and forensic analysis.

7. FUTURE SCOPE

While the current iteration of the Real-time AI CCTV Behavior Analysis system demonstrates robust performance and high accuracy, several avenues exist for future enhancement and expansion. A primary objective for subsequent development is the integration of cross-camera tracking via person Re-Identification (Re-ID) algorithms. This advancement would allow the system to maintain a subject's unique identifier as they move between different and overlapping camera feeds, enabling continuous, facility-wide trajectory mapping rather than isolated single-view analysis. Furthermore, the architecture could be evolved into a multimodal sensory network by incorporating acoustic anomaly detection. Fusing visual behavioral triggers with audio cues—such as glass breaking, gunshots, or aggressive shouting—would significantly increase the system's contextual awareness and further reduce false positive rates. To improve commercial scalability, future research will also focus on model quantization and edge-optimization techniques, facilitating the transition from high-end, centralized GPUs to low-power, decentralized edge TPU devices installed directly on the cameras. Finally, the analytical capabilities of the logic engine could be advanced by applying predictive machine learning models to the aggregated forensic CSV logs. This would transition the system from real-time alerting to long-term predictive threat modeling, allowing security administrators to forecast potential crowd crush events, identify temporal crime trends, and proactively address spatial vulnerabilities within the monitored environment.

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