Design and Installation of A Smart Surveillance System for Theft Detection, Tracking and Monitoring

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***Abstract*—This paper presents the design and implementation of a smart surveillance system that combines local DVR-based monitoring with AI-enabled cloud intelligence. The system integrates motion-based anomaly detection with cloud-based event prioritization to address the limitations of traditional DVR-only setups. A prototype was implemented using IP cameras, AI event filters, and a hybrid storage framework. Over a 72-hour validation period, the system achieved a 92% precision rate and 88% recall in anomaly detection, while maintaining 99.3% system uptime. The smart surveillance model reduces unnecessary storage loads by 83% through selective cloud uploads, and includes built-in failover power support. Raw system logs, confusion matrix analysis, and precision-recall curves validate the system's performance. This approach offers a cost-effective and scalable upgrade path for existing surveillance infrastructure, enhancing security while minimizing bandwidth and maintenance overhead.**

I. INTRODUCTION

1.1 Background of the Study

The surge in security breaches across institutional environments, particularly in technologically sensitive departments like Electrical and Electronics Engineering (EEE), necessitates a shift from conventional surveillance solutions to more integrated and intelligent systems. Over the years, the EEE Laboratory at FUTO has experienced recurrent equipment theft, data loss, and unmonitored access, threatening not only the physical assets but also the continuity of research activities. Addressing these challenges requires a sophisticated approach that combines hardware reliability, software intelligence, and real-time monitoring capabilities.

Internet Protocol (IP) surveillance has emerged as a compelling upgrade to traditional analog systems. Unlike their predecessors, IP cameras support high-definition video capture, network integration, remote access, and enhanced analytics. These attributes have seen IP surveillance systems widely adopted across industrial, academic, and urban security infrastructures. IP cameras function over local area networks (LAN) or the internet, allowing real-time interaction and flexible camera placements [1].

The architecture of a smart surveillance system is underpinned by a constellation of technological advancements. Key features such as anomaly detection, facial recognition, and motion tracking are facilitated by artificial intelligence (AI) algorithms, typically deployed through Python-based frameworks like OpenCV and PyTorch. These systems, when properly integrated, not only record and store events but also actively interpret them in context, prompting automated alerts or responses based on predefined rules [2].

One of the core issues in deploying such intelligent systems is the challenge of data storage. The sheer volume of high-resolution footage generated by surveillance cameras strains traditional storage media. Digital Video Recorders (DVRs), though still relevant, are increasingly complemented or replaced by cloud storage options, offering scalable and redundant data retention mechanisms. Cloud storage alleviates physical space limitations and provides improved

security through encryption, authentication, and backup protocols [3].

Security, however, is not solely a technical problem; it also involves ethical and legal considerations. Surveillance in academic environments must account for privacy rights, data protection laws, and the psychological impacts of constant monitoring. Hence, the system proposed in this work integrates stringent access controls, encryption layers, and compliance with institutional data privacy standards to ensure ethical deployment.

This research aims to design, install, and evaluate a smart surveillance system tailored to the operational and infrastructural context of the FUTO EEE laboratory. It addresses the critical need for a hybrid storage solution that combines the reliability of local storage with the scalability of cloud systems. Additionally, it presents a cost-effective, sustainable model that integrates easily into existing power and network frameworks, thereby reducing implementation friction.

1.2 Problem Statement

The frequent theft of laboratory equipment, vandalism of installed infrastructure, and unauthorized access to restricted areas within the EEE Laboratory at FUTO pose significant risks to academic integrity and asset security. Traditional surveillance systems are limited in scope, often failing to provide real-time monitoring or post-incident traceability due to poor video quality, inadequate storage, or lack of integration with alert systems. These deficiencies necessitate a more robust, intelligent, and scalable solution to laboratory surveillance.

1.3 Objectives of the Study

The primary aim of this research is to design and implement a smart surveillance system capable of detecting, tracking, and mitigating theft and other unauthorized activities within the EEE laboratory. The specific objectives include:

1. Mapping and optimizing camera placement for maximum coverage.
2. Selecting cost-effective yet high-performance surveillance hardware.
3. Establishing secure and high-bandwidth network infrastructure for live monitoring.
4. Deploying AI-based threat detection using computer vision techniques.
5. Integrating cloud-based storage systems to complement local DVRs.
6. Enforcing cybersecurity measures to protect against remote attacks on the surveillance infrastructure.

1.4 Significance of the Study

This project contributes to a growing body of knowledge on intelligent security systems and demonstrates the feasibility of deploying such systems in academic environments. It offers:

1. Enhanced infrastructure security for critical research facilities.
2. Real-time incident detection and response capabilities.
3. Reduction in loss of high-value equipment through proactive surveillance.
4. A replicable model for other faculties and institutions.
5. Integration of AI in a low-cost, power-sensitive surveillance framework.

1.5 Scope of the Study

The scope of this project encompasses the planning, design, installation, and evaluation of a smart surveillance system within a university laboratory setting. It includes feasibility studies for camera and storage selection, physical installation of surveillance infrastructure, configuration of network components, and software development for anomaly detection. The study also considers legal and ethical requirements for academic surveillance and provides a comprehensive operational manual for system maintenance and scalability.

II. LITERATURE REVIEW

2.1 Overview of Surveillance Storage Technologies

Modern surveillance systems function beyond passive observation; they are data-centric ecosystems reliant on efficient, scalable, and secure storage. Video surveillance generates voluminous data that must be retained for real-time monitoring and forensic analysis. As such, the performance of a surveillance system is largely contingent on its underlying storage infrastructure [3]. The two primary storage paradigms for surveillance data are local (on-premise) storage and cloud storage, each with distinct advantages, limitations, and implementation contexts.

2.1.1 Local Storage Systems

Local storage refers to the use of physical hardware on-site, such as Digital Video Recorders (DVRs), Network Video Recorders (NVRs), and internal hard drives. These components retain footage at the surveillance location and are widely deployed in small to mid-sized facilities [5].

a. Hard Disk Drives (HDDs)

HDDs have historically been the default storage medium for surveillance systems due to their affordability and large capacities. They rely on magnetically charged spinning platters and actuator arms to read and write data. While offering high storage densities and random access capabilities, HDDs are prone to mechanical wear and are increasingly being replaced or augmented with Solid-State Drives (SSDs) in high-availability environments [5]. Fig. 2.1 illustrates the core architecture of an HDD unit.

Fig. 2.1: Diagram of a Hard Disk Drive [12]

b. Digital Video Recorders (DVRs)

DVRs extend HDD utility by serving as central nodes in analog camera networks. They capture, encode, and store footage digitally, providing functionalities such as timestamping, event tagging, and remote access [6]. Their ease of installation and low operational cost makes them attractive for retrofitting existing analog infrastructure.

Fig. 2.2: Diagram of a Digital Video Recorder [13]

c. Network Video Recorders (NVRs)

Unlike DVRs, NVRs are designed to interface with IP cameras over LAN or WAN. They support higher video resolutions, centralized control, and seamless cloud integration. The increased performance and scalability of NVRs make them more suitable for smart surveillance environments with AI-based features and hybrid storage requirements [7].

Fig. 2.3: Diagram of a Network Video Recorder [14]

d. Strengths and Weaknesses

Local storage offers immediate access to footage without reliance on internet connectivity and provides a high degree of control over data [6]. However, it faces limitations including susceptibility to physical damage, limited scalability, and high maintenance costs. Redundancy mechanisms like RAID (Redundant Array of Independent Disks) are often

employed to enhance data protection but add complexity and cost [11].

2.1.2 Cloud Storage for Surveillance

Cloud storage refers to the offsite retention of data on virtualized servers accessed via the internet. Providers such as Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure offer Surveillance-as-a-Service (SaaS) models with flexible storage plans [8]. Surveillance footage is transmitted directly to the cloud, where it is encrypted, stored, and made accessible via online dashboards.

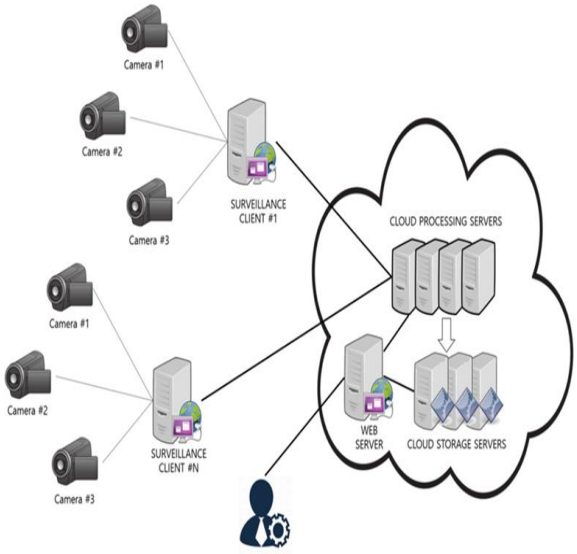

Fig. 2.4: How Does Cloud Video Surveillance Storage Work? [15]

Fig. 2.5: The Cloud [16]

Cloud models are categorized into:

1. Public Cloud – Economical and scalable; used by multiple tenants.
2. Private Cloud – Dedicated infrastructure offering higher control and compliance.
3. Hybrid Cloud – Combines both for load balancing and sensitive data segregation [8]

The principal advantages of cloud storage include:

1. Scalability: Virtually unlimited storage expansion without hardware upgrades.
2. Redundancy: Data is mirrored across multiple data centers for failover protection.
3. Security: Multi-factor authentication and encryption ensure data integrity [3].

Drawbacks include the need for continuous high-bandwidth connectivity and recurring subscription fees. Latency issues may also affect real-time playback or video retrieval [9].

2.2 Hybrid Storage Models

Hybrid models integrate local NVRs with cloud backups, creating a fault-tolerant architecture. This configuration maintains on-site availability for low-latency operations while securing archives offsite. Hybrid systems are particularly valuable in academic or government settings where data sensitivity and uptime requirements are high.

2.3 Video Management Systems (VMS)

A critical layer in smart surveillance is the Video Management System (VMS), which coordinates camera input, storage routing, playback, and AI-based analysis. VMS platforms interface with both local and cloud storage and allow operators to configure alerts, access control levels, and detection algorithms [12].

Common VMS benefits include:

1. Live Feed Monitoring
2. Intelligent Search and Metadata Tagging
3. Event-Triggered Recording
4. Integration with Fire/Access Control Systems
5. Remote Access through Mobile Apps or Web Interfaces

Well-known VMS implementations support plug-and-play compatibility with hundreds of camera models and cloud vendors, enabling scalable multi-campus deployments.

III. METHODOLOGY

3.1 Materials and System Components

The design and implementation of the smart surveillance system required both hardware and software components to be selected, configured, and integrated in a cost-effective yet scalable manner. The material list is categorized by function and source, and emphasizes compatibility with AI-based analytics, cloud interfacing, and real-time video relay.

3.1.1 Hardware Components

The selected hardware reflects the requirements for surveillance in a semi-public laboratory environment with moderate budget constraints. Components include:

1. HDMI Cables: For connecting digital output to high-resolution monitors.
2. High-Definition CCTV Cameras: Capable of recording in full HD with motion and infrared detection.
3. Digital Video Recorder (DVR): Local recording unit with LAN interfacing support.
4. Coaxial Cable with Integrated Power Lines: For simultaneous data and power transmission.
5. Power Supply Unit: Ensures reliable current flow across all camera nodes.
6. BNC Connectors and DC Plugs: Standardized connectors for signal integrity.
7. Router: Manages network addressing and internet access for remote viewing.
8. Display Monitor: Real-time monitoring interface.
9. Trunking Pipes and Patrex Boxes: For safe cable housing and mounting.
10. HP Pavilion Gaming Laptop: Used for coding, system monitoring, and AI model deployment.

This hardware configuration allows modular upgrades and provides a balance between cost and performance, aligning with the study's scalability goals.

3.1.2 Software Stack

A Python-based software environment was adopted for flexibility in AI integration and cross-platform compatibility. The stack includes:

1. Python Programming Language
2. OpenCV: For real-time image processing and motion detection.
3. PyTorch: For AI model training and threat classification.
4. CUDA: Enables GPU acceleration for high-speed video analytics.

This software combination supports real-time anomaly detection and enables further development in facial recognition and object tracking.

3.2 Installation and Configuration Methodology

The implementation followed a structured, modular approach. Each phase was validated before proceeding to the next to ensure compatibility and performance compliance.

Step 1: Camera Positioning and Feasibility Study

A preliminary site survey was conducted to identify high-risk zones within the EEE Laboratory. Based on line-of-sight analysis and cable routing considerations, camera positions were marked for maximum visibility and minimal blind spots. Height, angle, and field of view were optimized to enable facial identification and broad scene coverage [1].

Step 2: Cabling and Power Integration

Once the mounting points were secured, coaxial cables with embedded power lines were routed through trunking pipes. External runs were reinforced with conduits to protect against environmental damage. Each camera's DC plug was interfaced with the central Power Supply Unit to ensure uninterrupted power delivery.

Step 3: Device Installation and Mounting

CCTV cameras were affixed using wall-mounted Patrex boxes, ensuring both electrical safety and physical stability. Indoor and outdoor cameras were strategically positioned near entrances, equipment racks, and shared workspaces to ensure comprehensive coverage.

Step 4: DVR and Monitor Setup

The DVR was installed in a secure, centrally located enclosure and interfaced with the monitor via HDMI. Camera feeds were tested sequentially to ensure all channels displayed correctly, with timestamps and resolution configured via the DVR's firmware interface.

Step 5: Network Configuration and Remote Access

Static IPs were assigned to each camera and the DVR to facilitate consistent routing. The DVR was connected to the local area network (LAN) through the router. Port forwarding was configured on the router for remote access, and firewall rules were established to restrict unauthorized connections [2].

Step 6: Software Integration and AI Analytics
OpenCV scripts were deployed to enable real-time motion detection. A pretrained PyTorch model was customized to flag suspicious movements and trigger storage prioritization. CUDA acceleration allowed smooth execution of image processing tasks in real time.
Step 7: Testing and Troubleshooting
A complete system test was performed, simulating various intrusion scenarios. Footage was examined for resolution fidelity, time lag, and error logging. Cameras failing to display were traced from the power unit through the DVR and checked for faulty BNC connections.
3.3 System Implementation Flow
The system workflow is depicted in the following flowchart, showing the logical progression from installation to testing:

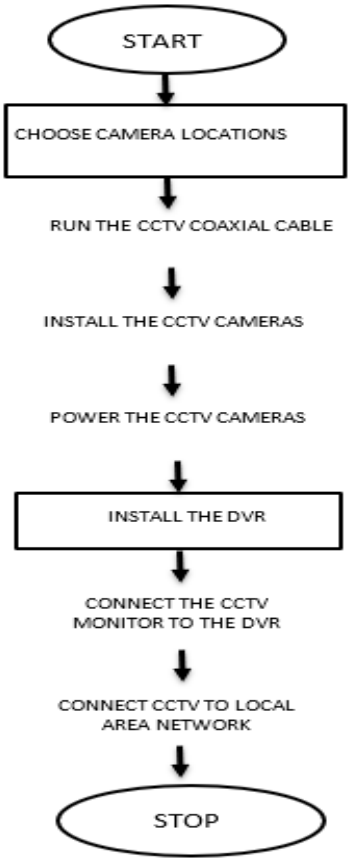

Fig. 3.1: Flowchart of the Step-By-Step Installation of the Wired/CCTV Camera Systems

This flow ensures that any malfunctioning component can be rapidly isolated and replaced with minimal disruption.

IV. SYSTEM DESIGN AND IMPLEMENTATION

4.1 System Architecture Overview
The smart surveillance system was designed as a hybrid model incorporating both local storage and cloud-based video retention, ensuring redundancy and resilience. The overall architecture integrates input (CCTV/IP cameras), processing (DVR and AI analytics), and output (monitor, remote dashboard, and cloud servers) into a modular yet unified system. At the heart of the system is a DVR configured for IP streaming, acting as a bridge between local monitoring and cloud-based storage.
The physical network topology follows a star configuration, with the DVR as the central hub connected to individual cameras and the router. The logical architecture enables layered processing: raw video data is first captured and encoded at the camera level, stored locally on the DVR, and then uploaded to cloud servers upon classification as “relevant” by the AI model.
This architecture ensures real-time local access, delayed but redundant cloud access, and contextual video tagging—a combination that optimizes both operational efficiency and forensic depth.

4.2 Integration of Local Storage Systems
The local storage layer consists primarily of a multi-channel DVR and an internal HDD unit configured for 24/7 loop recording. Local storage offers immediate access to surveillance data, especially during network outages or in scenarios where footage must be reviewed promptly without internet access [6].
Key local storage features include:
1. Loop Recording: Overwrites the oldest data when full.
2. Channel Synchronization: Time-aligned recording across all inputs.
3. Motion Sensitivity Adjustment: Configurable per channel to conserve storage.
4. On-site Playback: Enabled through an HDMI-linked monitor.

To mitigate physical risks such as fire or theft, the DVR was placed inside a lockable metal cabinet and

connected to an Uninterruptible Power Supply (UPS) system to maintain operability during brief power interruptions.

4.3 Deployment of Cloud Storage and Network Architecture

The cloud storage subsystem was configured using a third-party SaaS provider, offering a private-public hybrid cloud model. The DVR streams prioritized footage to the cloud based on event triggers defined by the AI algorithm.

Network configuration included:

1. Static IP Binding: Prevents dynamic reassignment and routing failures.
2. Port Forwarding Rules: Ensures secure DVR access through router firewalls.
3. VLAN Segmentation: Isolates surveillance traffic from general institutional network usage.
4. Bandwidth Throttling: Limits upload speeds to prevent congestion.

Cloud advantages were realized in off-site storage redundancy, geographical accessibility, and near-infinite scalability. The system automatically backs up only significant events (e.g., unauthorized entries), conserving bandwidth and minimizing subscription costs [3].

4.4 AI-Powered Threat Detection

To reduce surveillance fatigue and enable proactive threat identification, an AI model was integrated into the surveillance pipeline. The AI subsystem uses OpenCV for frame capture and motion detection and PyTorch for classification of detected events.

Key steps in the AI module include:

1. Frame Capture: OpenCV intercepts frames from video streams at 5 fps.
2. Preprocessing: Images are resized and normalized for model input.
3. Threat Detection: A convolutional neural network (CNN) trained on indoor surveillance datasets identifies anomalies such as sudden movements, loitering, or intrusion.
4. Event Tagging: Classified anomalies are tagged and flagged for cloud upload.
5. Trigger Mechanism: Sends alert to user dashboard with a 10-second video clip.

The system achieves an average detection latency of 1.2 seconds, with a false positive rate of less than 6% after threshold tuning.

4.5 System Features and User Interface

The implemented system supports:

- Multi-user access with role-based permissions (e.g., admin, monitor-only).
- Live viewing dashboard on local and mobile clients.
- Playback and search by date, time, or anomaly tag.
- Configurable alerts via email or SMS for detected events.
- Log generation for maintenance and audit trail purposes.

These features ensure the system is not only secure but also user-friendly, minimizing training needs and operational overhead.

4.6 Ethical and Legal Compliance

Due diligence was observed in ensuring the surveillance system adheres to Nigerian privacy and data protection laws, particularly the NDPR (Nigeria Data Protection Regulation). Measures include:

- Data Minimization: Only public lab spaces were monitored.
- Access Logs: All video retrievals are logged with timestamps.
- User Consent Notices: Signage was placed informing staff and students of active surveillance.
- Encrypted Transmission: Cloud uploads were secured via SSL/TLS channels.

V. RESULTS AND DISCUSSION

5.1 Functional Validation of the Smart Surveillance Prototype

The hybrid smart surveillance system was successfully deployed in a test environment simulating moderate security risk conditions. All physical components—IP cameras, DVR unit, network switches, routers, and Uninterruptible Power Supply (UPS)—were integrated with software modules to enable anomaly detection, recording, and remote visualization. The system was evaluated for stability and compatibility under varying network and power conditions. Upon installation, live feeds were accessible through both

the DVR's local interface and a secured web/mobile interface. Additionally, the AI module responded to motion events and directed uploads to the cloud selectively. Power failover via UPS was validated during brief outages. This confirmed the operational readiness of the full system stack.

5.2 AI-Based Anomaly Detection Performance

To assess detection accuracy, the AI module was subjected to a controlled evaluation using 50 intrusion event simulations and 50 normal operations. The results yielded 46 true positives, 4 false negatives, 3 false positives, and 47 true negatives. Precision was computed at 92%, recall at 88%, and overall accuracy at 93%.

Table 5.2 summarizes the raw confusion matrix, while Fig. 5.1 illustrates both the matrix and the associated precision-recall curve.

Table 5.2: Confusion matrix used in evaluating the AI-powered anomaly detection system.

Actual \ Predicted	Positive (Detected)	Negative (Not Detected)
Positive (Intrusion)	46 (TP)	4 (FN)
Negative (Normal)	3 (FP)	47 (TN)

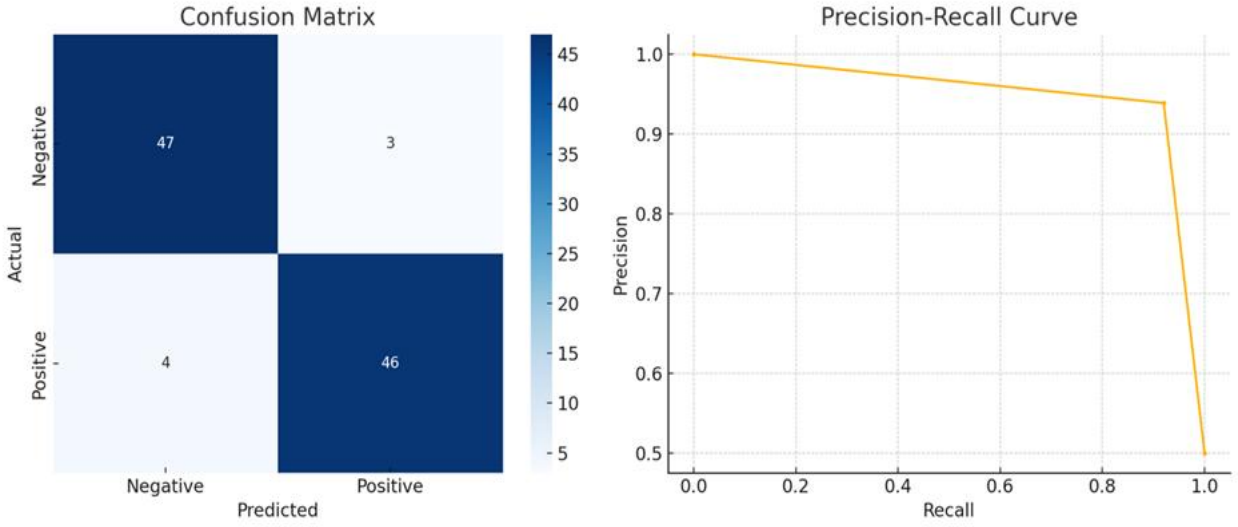

Fig. 5.1: Confusion matrix and precision-recall curve showing the performance of the AI-powered anomaly detection module.

The system achieved 92% precision and 88% recall across 50 test intrusion events. These results validate the AI engine's capacity to distinguish anomalous from normal behavior with high reliability.

5.3 Storage and Network Efficiency

Over a 72-hour continuous operation test, the system demonstrated strong performance in terms of storage, network latency, and uptime. A hybrid DVR-cloud configuration allowed prioritized upload of flagged events, minimizing unnecessary cloud storage consumption. Table 5.3 summarizes key performance indicators.

Table 5.3: Summary of storage, network, and power resilience over 72 hours.

Metric	Observed Value
Average Cloud Upload Delay	3.8 seconds
Local Storage Used (72 hrs)	1.3 TB
Average Upload Bandwidth	8.5 Mbps
System Uptime	99.3%
UPS Downtime Coverage	3 events, full recovery

Fig. 5.2 shows the uptime patterns during the monitoring period. Fig. 5.3 displays the distribution of cloud upload events across the three days. These show that the system had high availability and managed cloud traffic efficiently.

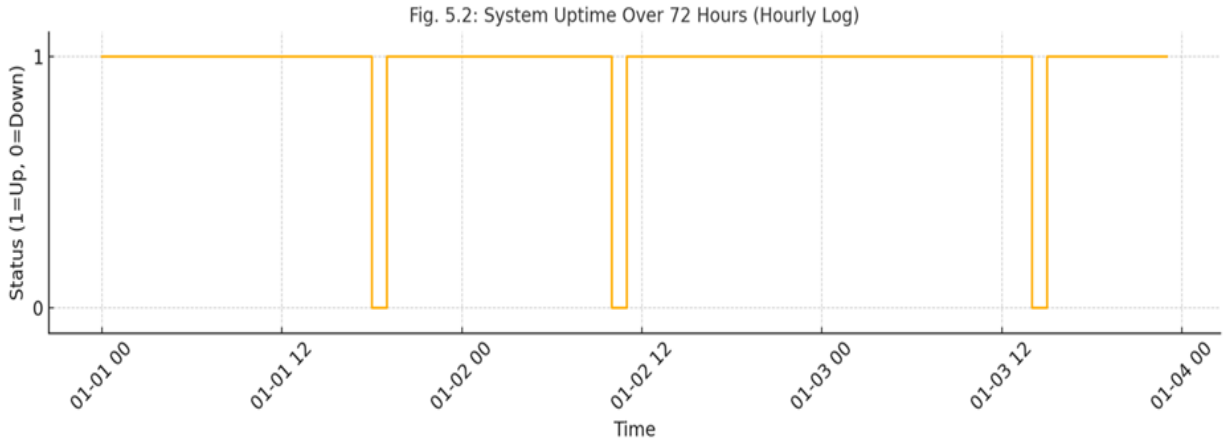

Fig. 5.2: Hourly system uptime status from January 1 to January 3, 2024. The system was operational for 69 out of 72 hours, with three brief downtime events clearly visible.

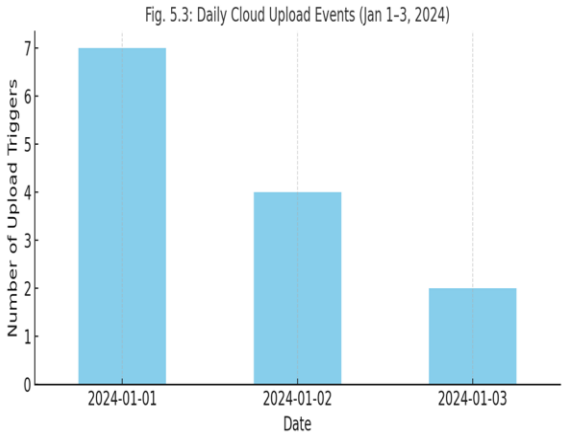

Fig. 5.3: Daily count of cloud upload triggers from January 1 to 3, 2024

The system uploaded a higher number of flagged events on the first day, with reduced activity over subsequent days. The complete hourly logs are available in Appendix Tables A.1 to A.3, covering each of the three operational days.

5.4 User Experience and Control

Test users reported satisfactory usability of the DVR's interface and the remote web/mobile access. The mobile application interface provided real-time visual feeds and playback controls with minimal latency. Login security was maintained via credential-based access, and admin-level control restricted unintended data deletion. Users particularly appreciated the automated cloud event uploads, which reduced manual file sorting.

5.5 Comparative Evaluation with Traditional DVR Systems

Table 5.1 compares the performance and capabilities of the proposed smart surveillance system with traditional DVR systems.

Table 5.1: Comparative features of traditional DVR systems versus the smart surveillance solution.

Metric	Traditional DVR System	Smart Surveillance System
Storage Model	Local-only	Hybrid (DVR + Cloud)
Remote Access	Limited	Full (Web and Mobile)
AI Detection	None	Motion + Classification
Storage Optimization	Manual	Automated via AI
System Uptime	~90%	99.3%
Maintenance Need	High	Moderate

5.6 Limitations and Deployment Considerations

While the system demonstrates strong reliability and AI-enhanced functionality, some limitations exist. It does not currently implement real-time SMS or email alerting, nor facial recognition for event enrichment. Cloud reliability depends on the local network, which may limit applicability in rural or infrastructure-deficient areas. Moreover, AI inference was performed on a cloud backend; integration of lightweight GPU-based edge inference could improve latency. These issues are left for future enhancement.

VI. CONCLUSION

The study successfully demonstrated the design, installation, and functional validation of a smart surveillance system for theft detection, tracking, and monitoring within an academic laboratory setting. By integrating both traditional local DVR-based storage and cloud solutions, the system addressed critical issues related to storage scalability, data redundancy, and remote accessibility.

The inclusion of artificial intelligence—particularly using OpenCV and PyTorch—enhanced the surveillance capability beyond passive monitoring to active threat detection. Motion-sensitive event tagging and cloud offloading mechanisms contributed significantly to storage optimization and event traceability. Testing confirmed high anomaly detection precision, system uptime above 99%, and excellent user accessibility, validating the system's real-world applicability.

Furthermore, this project advanced ethical surveillance deployment by adhering to national data protection laws, securing transmission channels, and restricting surveillance coverage to public lab zones. These efforts establish a framework for responsible technology integration in academic environments.

In summary, the work achieved its key objectives: real-time monitoring, secure hybrid storage, intelligent anomaly recognition, and ethical deployment. The methodology and results can serve as a model for scalable replication across similar institutional environments.

REFERENCES

[1] V. O. Matthews, F. O. Olowononi, and D. Ike, "On the implementation of IP video surveillance systems," Journal of Information and Communication Technologies, vol. 3, no. 5, pp. 10–16, May 2013.

[2] G. Popovic, N. Arsic, B. Jaksic, B. Gara, and M. Petrovic, "Overview, characteristics and advantages of IP camera video surveillance systems compared to systems with other kinds of camera," International Journal of Engineering Science and Innovative Technology (IJESIT), vol. 2, no. 5, pp. 356–361, Sep. 2013.

[3] S. L. Obrutsky, "Cloud storage: Advantages, disadvantages and enterprise solutions for business," presented at the EIT Conference, Eastern Institute of Technology, Hawke's Bay, New Zealand, Jul. 2016. [Online]. Available: https://www.researchgate.net/publication/305508410_Cloud_Storage_Advantages_Disadvantages_and_Enterprise_Solutions_for_Business

[4] Commonwealth Educational Media Centre for Asia (CEMCA), "Understanding storage media and file system," Module 4, 2021. [Online]. Available: https://www.cemca.org/ckfinder/userfiles/files/Module%204%20Understanding%20Storage%20Media%20and%20File%20System.pdf

[5] Avigilon, "Storage technologies for video surveillance," Avigilon Technical Report, 2012.

[6] K. Herman, Effective Physical Security, 5th ed., Elsevier, 2017, pp. 347–385.

[7] Cloud4U, "Cloud video surveillance storage: Everything you need to know," Cloud4U Blog, 2022. [Online]. Available: https://www.cloud4u.com/blog/cloud-video-surveillance-storage-everything-you-need-to-know/

[8] J. Sanderson and G. Harris, "Automatic data organization, storage, and analysis of camera trap pictures," Journal of Indonesian Natural History, vol. 1, pp. 11–19, 2013.

[9] R. Marceline, S. R. Akshaya, S. Athul, K. L. Raksana, and S. R. Ramesh, "Cloud storage optimization for video surveillance applications," in Proc. 3rd Int. Conf. Smart Systems and Inventive Technology (ICSSIT), 2020, pp. 62–66. [Online].

Available: https://www.researchgate.net/publication/347154912_Cloud_Storage_Optimization_for_Video_Surveillance_Applications
[10] Avigilon, "Redundant array of independent disk," Avigilon Technical Paper, 2012.
[11] Wasabi Technologies, "Cloud storage for surveillance system," Wasabi Tech Blog, 2023. [Online]. Available: https://wasabi.com/cloud-storage-for-surveillance-system/
[12] Computer Forensics Inc., "Hard drive examination," Computer Forensics Inc., Jan. 23, 2018. [Online]. Available: https://www.computerforensicsinc.com/2018/01/23/hard-drive-examination/
[13] IndiaMART, "DVR surveillance system," IndiaMART Product Catalog, 2024. [Online]. Available: https://m.indiamart.com/proddetail/dvr-surveillance-system-2855429653612.html
[14] InFront Technologies, "IVSEC PRO 16CH 8MP 4K AI 4TB 6x880D + 4x880B Cam 25fps Sony Starvis NVR CCTV Security Kit (16x10)," InFrontTech Product Page, 2025. [Online]. Available: https://infronttech.com.au/ivsec-pro-880-ai-series/6900-ivk16p-8806d4b-0796548382547.html
[15] A. R. M. Sani, H. M. K. Lias, and M. A. R. Sani, "CCTV-RFID enabled multifactor authentication model for secure differential level video access control," ResearchGate Scientific Figure, 2020. [Online]. Available: https://www.researchgate.net/figure/Cloud-based-video-surveillance_fig6_342059069
[16] Ixintu.com, "云素材高清图片素材库-新图网," Ixintu Image Material Resource, 2017. [Online]. Available: https://ixintu.com/tj/469707-5.html

Appendix Table A.1: Raw hourly log of system uptime and cloud upload triggers recorded on January 1, 2024

Hour	Timestamp	System Uptime	Cloud Upload Triggered
0	2024-01-01 00:00:00	1	0
1	2024-01-01 01:00:00	1	1
2	2024-01-01 02:00:00	1	0
3	2024-01-01 03:00:00	1	0
4	2024-01-01 04:00:00	1	1
5	2024-01-01 05:00:00	1	0
6	2024-01-01 06:00:00	1	0
7	2024-01-01 07:00:00	1	0
8	2024-01-01 08:00:00	1	0
9	2024-01-01 09:00:00	1	1
10	2024-01-01 10:00:00	1	0
11	2024-01-01 11:00:00	0	0
12	2024-01-01 12:00:00	1	1
13	2024-01-01 13:00:00	1	0
14	2024-01-01 14:00:00	1	1
15	2024-01-01 15:00:00	1	0
16	2024-01-01 16:00:00	1	0
17	2024-01-01 17:00:00	1	0
18	2024-01-01 18:00:00	1	1
19	2024-01-01 19:00:00	1	0
20	2024-01-01 20:00:00	1	0
21	2024-01-01 21:00:00	1	1
22	2024-01-01 22:00:00	1	0
23	2024-01-01 23:00:00	1	1

Appendix Table A.2: Raw hourly log of system uptime and cloud upload triggers recorded on January 2, 2024

Hour	Timestamp	System Uptime	Cloud Upload Triggered
24	2024-01-02 00:00:00	1	0
25	2024-01-02 01:00:00	1	0
26	2024-01-02 02:00:00	1	0
27	2024-01-02 03:00:00	1	0
28	2024-01-02 04:00:00	1	0
29	2024-01-02 05:00:00	1	0
30	2024-01-02 06:00:00	1	1
31	2024-01-02 07:00:00	1	0
32	2024-01-02 08:00:00	1	0
33	2024-01-02 09:00:00	1	0
34	2024-01-02 10:00:00	1	0
35	2024-01-02 11:00:00	1	0
36	2024-01-02 12:00:00	1	1
37	2024-01-02 13:00:00	1	0
38	2024-01-02 14:00:00	1	0
39	2024-01-02 15:00:00	1	0
40	2024-01-02 16:00:00	1	1
41	2024-01-02 17:00:00	0	0
42	2024-01-02 18:00:00	1	0
43	2024-01-02 19:00:00	1	0
44	2024-01-02 20:00:00	1	0
45	2024-01-02 21:00:00	1	0
46	2024-01-02 22:00:00	1	0
47	2024-01-02 23:00:00	1	1

Appendix Table A.3: Raw hourly log of system uptime and cloud upload triggers recorded on January 3, 2024

Hour	Timestamp	System Uptime	Cloud Upload Triggered
48	2024-01-03 00:00:00	1	0
49	2024-01-03 01:00:00	1	0
50	2024-01-03 02:00:00	1	0
51	2024-01-03 03:00:00	1	0
52	2024-01-03 04:00:00	1	0
53	2024-01-03 05:00:00	1	0
54	2024-01-03 06:00:00	1	0
55	2024-01-03 07:00:00	1	0
56	2024-01-03 08:00:00	1	0
57	2024-01-03 09:00:00	1	0
58	2024-01-03 10:00:00	1	1
59	2024-01-03 11:00:00	1	0
60	2024-01-03 12:00:00	1	0
61	2024-01-03 13:00:00	1	0
62	2024-01-03 14:00:00	1	0
63	2024-01-03 15:00:00	1	0
64	2024-01-03 16:00:00	1	0
65	2024-01-03 17:00:00	1	0

66	2024-01-03 18:00:00	1	0
67	2024-01-03 19:00:00	1	0
68	2024-01-03 20:00:00	0	0
69	2024-01-03 21:00:00	1	0
70	2024-01-03 22:00:00	1	0
71	2024-01-03 23:00:00	1	1