Dissertation on

"Detection And Mitigation Of Replay Attack in CCTV Systems"

Submitted in partial fulfilment of the requirements for the award of degree of

Bachelor of Technology
in
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UE22CS441A – Capstone Project Phase - 3

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CERTIFICATE

This is to certify that the dissertation entitled

'Detection And Mitigation Of Replay Attacks in CCTV systems'

is a bonafide work carried out by

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In partial fulfilment for the completion of seventh semester Capstone Project Phase - 3 (UE22CS441A) in the Program of Study -Bachelor of Technology in Computer Science and Engineering under rules and regulations of PES University, Bengaluru during the period Aug 2025 – Nov. 2025. It is certified that all corrections / suggestions indicated for internal assessment have been incorporated in the report. The dissertation has been approved as it satisfies the 7th semester academic requirements in respect of project work.

Signature Dr.Manju Professor	Signature Sandesh B J Chairperson	Signature Dr. Sridhar Registrar

External Viva

Name of the Examiners	**Signature with Date**
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DECLARATION

We hereby declare that the Capstone Project Phase - 2 entitled **"Detection And Mitigation Of Replay Attacks In CCTV Cameras"** has been carried out by us under the guidance of Dr.Manju and submitted in partial fulfillment of the course requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** of **PES University, Bengaluru** during the academic semester January – May 2025. The matter embodied in this report has not been submitted to any other university or institution for the award of any degree.

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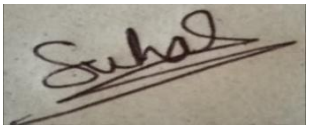
PES2UG22CS590	**Suhas Venkata**	

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ABSTRACT

CCTV systems are an absolute necessity in modern surveillance, but their use is very vast covering everything from banking to transportation, healthcare to public safety. But these systems are becoming increasingly vulnerable to cyber threats, where replay attacks being one of the main threats. An alteration of video authentication can happen due to replay attacks, which involve capturing any valid stream and then re-recording it and putting it into the system to deceive the system and providing access to the camera, which could change the video and compromise the whole security of the system. This highlights the need for better security especially around communication protocols that which aren't strict enough

To tackle these challenges, we are proposing an AI-based detection and response system specifically designed to mitigate replay attacks in CCTV networks. By integrating machine learning and cryptographic security measures, the system aims to detect, prevent, and respond to replay attacks in real-time, due to which we can rely on CCTV systems without any fear.

The main components are:

1. AI-Powered Anomaly Detection: We will be utilizing ML models to analyse video streams and network traffic for anomalies that indicate replay attacks, such as inconsistencies in timestamps and frame sequences.

2. Secure Communication Protocols: We plan on implementing encryption and/or digital signatures in order to ensure secure data transmission and to verify that video streams are not tampered with, and that only legitimate data is processed.

3. Real-Time Automated Response: We will be working on a threat response module that takes appropriate action in near-real time upon detecting an attack, including alerting administrators, isolating compromised devices, and blocking malicious traffic.

4. Modular Design: We will try our best to design this system so that it can seamlessly integrate with existing CCTV systems, ensuring compatibility with a lot of hardware and software configurations.

This project will involve a comprehensive vulnerability assessment of current CCTV systems, training ML models on datasets simulating replay attacks, and testing in controlled environments. The goal is to make a scalable, effective and user-friendly system.

It is anticipated that effective implementation will yield better detection of replay attacks, thus resulting in enhanced security in CCTV systems, reduced susceptibility to cyber threats, and thus making surveillance technologies more reliable. Hence the project is a step forward towards intelligent, adaptable, and self-Secured surveillance technologies

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CHAPTER 1

INTRODUCTION

CCTV systems have become a key part of security setups. They provide real-time surveillance and recording to spot threats and safeguard important places like banks, data centers, and public spaces. But these systems are susceptible to replay attacks-a sophisticated cyber-attack where hackers intercept and capture real video footage or commands sent by the system, and retransmit the data at some point in the future. By replaying old footage or commands, attackers can deceive systems into displaying false information as live data and thus bypass mechanisms for real-time monitoring.

Replay attacks exploit the weaknesses of improperly secured communication protocols or outdated or legacy CCTV systems that lack the contemporary security features of robust encryption, authentication, and tamper detection. These could have extremely negative effects, such as:

Avoiding Real-Time Monitoring

This would enable an attacker to substitute prerecorded video for live video streams in a way that conceals their ongoing activities, leading the system to assume that everything is OK and normal until intrusions or unauthorised actions actually occur. The system's capacity to identify and react to threats in real time has been compromised.

Establishing Blind Spots in Security

In order to conceal unwanted access or movements around sensitive locations, such as server rooms, bank vaults, or restricted airport areas, among others, it can also enable hackers to continuously play back old video. This can result in unnoticed intrusions that cause theft, sabotage, or illegal access to important data and equipment.

Evidence Manipulation:

In many court cases and investigations, surveillance footage serves as evidence. Replay attacks can change original recordings, leading to incorrect timelines, events that never took place, or missing data. These issues can harm investigations and endanger legal proceedings.

Taking Advantage of Access Control Systems

Surveillance footage is often used as evidence in court cases and investigations. Replay attacks can change the original recordings. This results in incorrect timelines that show events that never happened or missing data. These issues could hurt investigations and put legal proceedings at risk.

Focusing on Legacy Systems

The firmware of most CCTV cameras is out of date. This puts them at risk. These cameras can be easily targeted by attackers. They can exploit both the system's digital and physical parts. To prevent replay attacks, we must ensure that all protocols are followed and that all firmware is updated.1.1 Project Workflow

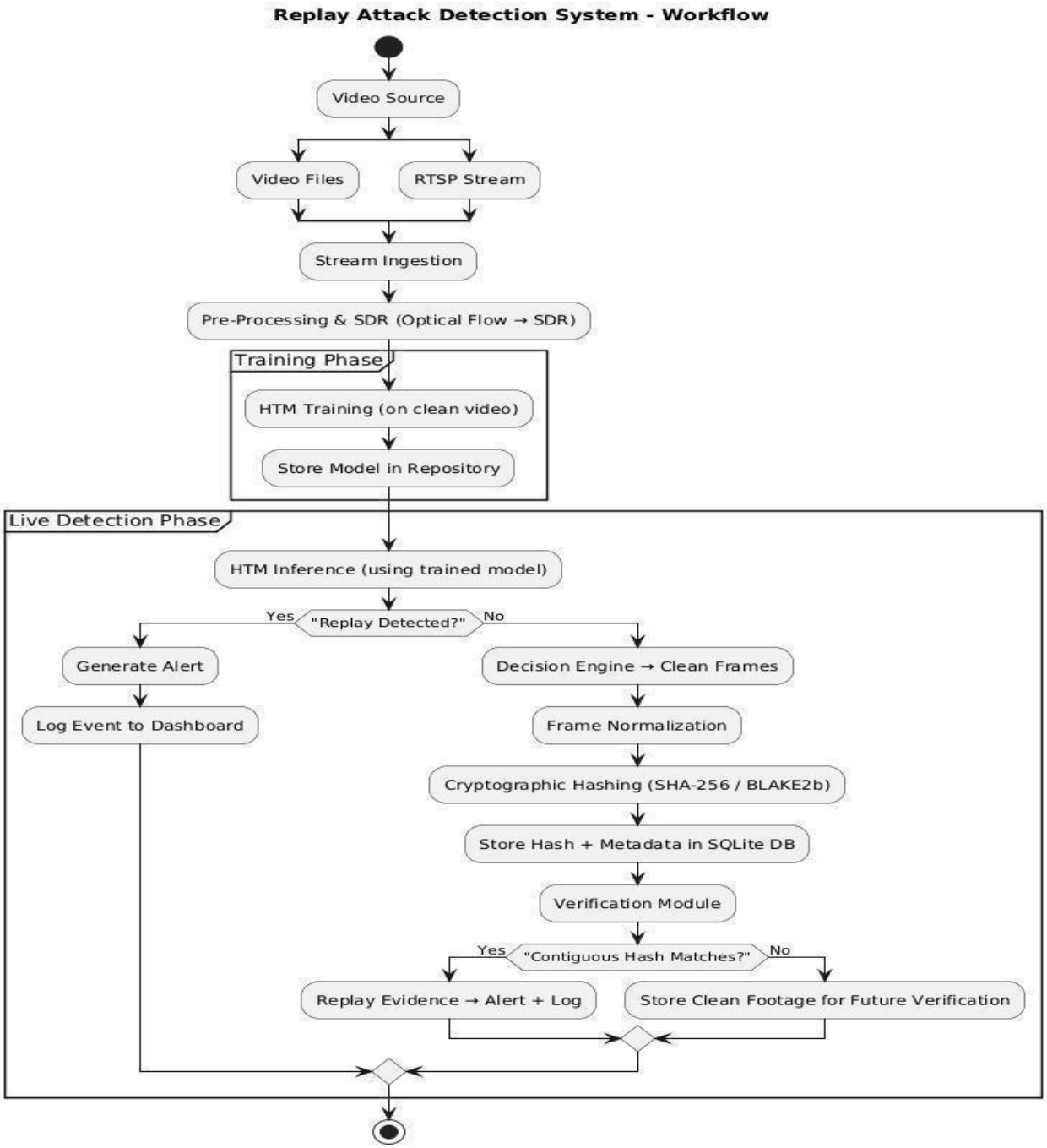

Fig 1.1 Project Workflow

As showed in Fig 1.1, Training and live detection are the two main stages of the replay attack detection system workflow. In the training phase, HTM models are developed using clean footage by taking in video sources like stored files or RTSP streams. These sources are pre-processed with optical flow and SDR encoding. The trained models are saved in a repository for future use. During the live detection phase, the trained HTM model processes incoming video streams and generates anomaly scores. Clean frames are normalized, hashed with cryptographic functions like SHA-256 or BLAKE2, and stored in a SQLite database along with metadata. The decision engine triggers alerts and logs the event if it suspects a replay. Next, a verification module compares the new frame hashes to the stored ones. Matches in a row suggest replay evidence, which gets flagged and sent to the alert system. Scattershot matches are seen as incidental and kept as clean. This integrated workflow ensures both long-term integrity verification and real-time anomaly detection of surveillance footage.

CHAPTER 2

PROBLEM STATEMENT

CCTV systems are widely used in today's security situations to protect important places like public areas, transit hubs, and banks. Replay attacks, a type of complex cyberattack, can now target these systems. Replay attacks involve capturing a real, live video feed and then replaying that recorded footage to the monitoring system. This tactic tricks the system into believing the scene is current and harmless, allowing illegal activities to go unnoticed.

The main issue is the difficulty in telling apart replayed video from actual live feeds. Old CCTV systems depend on outdated protocols. They usually do not have strong integrity controls or real-time authentication options. Furthermore, replay attacks compromise the overall security of monitored areas, cause time response delays, and invalidate the assurance obtained from automated monitoring systems.

Moreover, the diversity in sources of video input, variation in quality, and unpredictability of stream protocol make it rather complicated to lay out a universal framework for detecting integrity and authenticity in the streaming input. Therefore, minor variance that may be introduced by a mischievous agent can easily go unnoticed or even be misunderstood for legitimate normal variation and amplify the risks for undetectable security hole.

CHAPTER 3

LITERATURE REVIEW

3.1 "A Data-Driven Framework for Verified Detection of Replay Attacks on Industrial Control Systems"

3.1.1 Introduction

The paper proposes a two-stage detection and verification framework for detecting replay attacks in industrial control systems. The methodology includes:

- Real-time monitoring of sensor data using matrix profile-based change-point detection.
- Spatio-temporal feature extraction using short-time Fourier transform (STFT) to create spectrograms.
- ConvLSTM-AE (Convolutional Long Short-Term Memory Autoencoder) to verify replay attacks through reconstruction error from normal data.

3.1.2 Characteristics and Implementation

- Offers a two-phase framework for detection and verification.
- Stage 1 (Detection Real-time sensor data stream monitoring is accomplished through matrix profile-based change point detection.
- Stage 2 (Verification): Short-time Fourier transform (STFT) is used to extract spatiotemporal features, and a ConvLSTM-AE (Convolutional LSTM Autoencoder) is applied to confirm replay attacks via reconstruction error.
- Made to be deployed in real-time ICS environments

3.1.2 Features

- In a variety of scenarios, the suggested framework effectively identifies and validates replay attacks in real time.
- A Tennessee Eastman Process simulation model was used to show its effectiveness. The results indicated a 100% verification rate for detecting replay attacks.
- The system's dependability is demonstrated by its low false alarm rate and detection delay metrics.

3.1.3 Evaluation

- The framework proposed in this paper successfully detects and verifies replay attacks in real-time in different scenarios.
- Demonstrated effectiveness using a Tennessee Eastman Process simulation model, with results showing a 100% verification rate for replay attack detection.
- Low false alarm rate and detection delay metrics show the system's reliability.

3.2 "Replay Attack Detection for Cyber-Physical Control Systems: A Dynamical Delay Estimation Method"

3.2.1 Introduction

Overview

The authors proposed a Dynamical Delay Estimation (DDE) technique that combines data-driven methods with system dynamics. They estimated and monitored delays between system inputs and outputs using sliding window methods. They used a window-adaptive approach for real-time detection and included a randomized algorithm to initialize delay estimates. They searched for anomalies that could indicate replay attacks by focusing on time-series correlation and changes in delay. Dong Zhao, Bo Yang, Yueyang Li, and Rui Zhang wrote this paper, published in IEEE Transactions on Industrial Electronics. It addresses the growing issue of replay attacks in cyber-physical systems (CPS), where attackers introduce previously recorded signals to deceive monitoring and control systems. To identify such attacks, the authors propose a new Dynamical Delay Estimation (DDE) technique that utilizes both system dynamics and data-driven analysis.

3.2.2 Characteristics and Implementation

- Robustness: Capable of functioning in noisy environments and during network interruptions.
- Hybrid Design: Combines data-driven anomaly detection with the behavior of physical systems.
- Comparative Benchmarking: Evaluated against several ML models, including SVM, Isolation Forest, LOF, and LSTM.
- High Accuracy: ML baselines reached an F1-score of 91.2%, and detection accuracy of 90.79% was achieved.

3.2.3 Features

- Robustness: Works well even in noisy conditions and network disruptions.
- Hybrid Design: Combines physical system dynamics with data-driven anomaly detection.
- Comparative Benchmarking: Assessed against several ML models, including SVM, Isolation Forest, LOF, and LSTM.
- High Accuracy: Reached 90.79% detection accuracy. ML baselines achieved an F1-score of 91.2%.

3.2.4 Evaluation

- Using a distillation column and a realistic CPS environment, researchers verified the technique through experiments.
- Outperforming conventional threshold-based techniques, the results showed strong resilience to noise and network delays.
- A fair comparative analysis was made possible by the inclusion of ML baselines, demonstrating that DDE can compete with the most advanced anomaly detection models.

3.3 "Lightweight 3D-StudentNet for Defending Against Face Replay Attacks"

3.3.1 Introduction

Paper Authors - Preethi Jayappa Seegahalli and B. Niranjana Krupa; published in - Journal of Imaging and Video Processing; in 2024. Deals with face replay attacks, which arise when the attackers use previously recorded facial videos to spoof an authentication system. This paper introduces a light-weight deep learning model which achieves a good balance between accuracy and computational efficiency; making it suitable for practical deployment.

3.3.2 Characteristics and Implementation

- Presents 3D-ArrowNet, a deep neural network that records facial video sequences' temporal and spatial characteristics.
- Proposes 3D-StudentNet, a simplified version that uses knowledge distillation to reduce model size and complexity without sacrificing performance.
- Improves the ability to distinguish between real and fake faces, especially in texture analysis, by utilising HSV colour space features.
- Tested for robustness using a combined dataset and the Replay-Mobile dataset.

3.3.3 Features

- High accuracy - 96.42% accuracy with an ACER (Average Classification Error Rate) of 0.45 and 100% accuracy on the Replay-Mobile dataset were attained.
- Generalization: The accuracy on aggregated datasets was 99.23%. This shows versatility across different sources.

- Lightweight Design: Compared to the original 3D-ArrowNet, knowledge distillation significantly reduces the computational load.
- Color-Texture Sensitivity: HSV-based feature extraction improves the ability to identify small spoofing artifacts.

3.3.4 Evaluation

- Showed outstanding results on benchmark datasets.

- Outperformed several current replay attack detection techniques in terms of error rate and accuracy.
- Demonstrated that large 3D CNNs can be effectively compressed using knowledge distillation without losing much accuracy.
- Proven ability to tell apart real and fake faces in controlled settings..

3.4 "An Enhanced Deep Learning Approach for Preventing Replay Attacks in Wireless Sensor Networks"

3.4.1 Introduction

Authors: Rajaram Pitchimuthu, Sathishkumar A., and Khadirkumar N.; published in Solid State Technology, Volume 63, Issue 4 (2020). This paper focuses on preventing replay attacks in Wireless Sensor Networks (WSNs). In these attacks, intruders exploit packet re-transmission to disrupt communication or impersonate real nodes. The authors propose a hybrid deep learning method that combines sequence modeling and decision-based classification to improve detection accuracy.

3.4.2 Characteristics and Implementation

- Presents a hybrid model that combines decision trees and Long Short-Term Memory (LSTM) networks.
- Identifies replayed traffic using key features such as packet length and inter-packet gaps.
- Uses the Fast Fourier Transform (FFT) and Gaussian blur on multimedia packets to extract features and reduce noise.
- For replay attack detection in WSNs, the ASV Spoof 2017 dataset was used for training and validation.

3.4.3 Features

- High Precision: A 0% error rate was achieved for packet replay detection on both the development and evaluation datasets.
- Robust Classification: A True Positive Rate (TPR) of 99% and a False Positive Rate (FPR) of 0% were reached using decision trees.
- Hybrid Strength: Decision trees provide clear classification, while LSTM captures temporal dependencies.
- Noise Resilience: Using FFT and Gaussian blur as preprocessing methods improves resilience to noisy multimedia packets.

3.4.4 Evaluation

- High Precision: A 0% error rate was achieved for packet replay detection on both the development and evaluation datasets.
- Robust Classification: A True Positive Rate (TPR) of 99% and a False Positive Rate (FPR) of 0% were reached using decision trees.
- Hybrid Strength: Decision trees provide clear classification, while LSTM captures temporal dependencies.
- Noise Resilience: Using FFT and Gaussian blur as preprocessing methods improves resilience to noisy multimedia packets

3.5 "Grid HTM: Hierarchical Temporal Memory for Anomaly Detection in Videos"

3.5.1 Introduction

Authors: Vladimir Monakhov, Pål Halvorsen, Vajira Thambawita, and Michael A. Riegler. This paper explores the use of Hierarchical Temporal Memory (HTM) in video surveillance for anomaly detection. HTM offers explainability, online learning, and resistance to noise. This is different from deep learning methods, which often struggle with noise sensitivity, changes in data patterns, and the need for large amounts of data. The paper introduces Grid HTM, a new architecture aimed at adapting HTM for complex video anomaly detection tasks.

3.5.2 Characteristics and Implementation

- Grid HTM Architecture: This design divides the input frame into a grid of cells. Each cell has its own Temporal Memory (TM) and Spatial Pooler (SP). This setup broadens the basic HTM.
- Segmentation Preprocessing: This method changes video frames into Sparse Distributed Representations (SDRs) suitable for HTM by using segmentation. An example is PointRend with a ResNet-101 backbone.
- Learning Mechanism:
    - SP extracts semantically meaningful features.
    - TM predicts typical sequences by learning the temporal patterns of objects (such as cars and people).

- Calibration Phase: Needs a first phase during which the system merely learns patterns and doesn't detect anomalies.

3.5.3 Features

- Noise Tolerance: HTM's online education adjusts to shifting data distributions.
- Explainability: The locations of anomalies are indicated by grid-based anomaly scores.
- Flexibility: Parallelisation and scalability are made possible by the independent configuration of each grid cell.
- Temporal Modelling: Improves motion capture in high-framerate videos by incorporating multistep temporal patterns.
- Use Case: Semi-active surveillance, which lowers the need for manpower by having operators only examine segments that have been flagged.
- Aggregation Functions: Examines the aggregation of mean versus non-zero mean anomaly scores across grid cells.

3.5.4 Evaluation

- Tested using stationary cameras and the VIRAT dataset.
- Found both synthetic (repeated frames) and technical (frame skips, freezes) anomalies.
- Unusual object behaviour, such as cars standing motionless in odd positions, was effectively highlighted by visual anomaly maps.
- Proved that, without direct supervision, Grid HTM is capable of learning typical traffic patterns and identifying irregularities.

3.6 "Detection, Differentiation and Localization of Replay Attack and False Data Injection Attack Based on Random Matrix"

3.6.1 Introduction

Authors - Yuehao Shen and Zhijun Qin; published in - Scientific Reports (2024). Addresses the challenge of defending cyber-physical power systems (CPPS) against two major cyber-attacks: Replay Attacks and False Data Injection Attacks (FDIA). Unlike most prior works that focus on detecting only one type of attack, this study proposes a unified framework capable of detecting, differentiating, and localizing both types of attacks simultaneously, even under noisy measurement conditions.

3.6.2 Characteristics and Implementation

- Two-Stage Framework:
    - Forecasting Stage: Short-term load and renewable power generation forecasting (using Random Forest + LSTM ensemble for load, and GEN-BP neural network for wind power).
    - Detection Stage: Create a random matrix using the differences between the real-time and predicted measurements. To find anomalies, use Linear Eigenvalue Statistics (LES) and Random Matrix Theory (RMT).
- Differentiation & Localization:
    - To differentiate replay attacks from FDIA, SVD-CNN (Singular Value Decomposition + Convolutional Neural Network) is introduced.

- A metric derived from eigenvalue analysis is used to pinpoint which meters are comprised during FDIA

- A sliding time window mechanism captures sequential correlations, which improves detection reliability.

3.6.3 Features

- Noise Tolerance: RTM effectively suppresses Gaussian noise, which improves the robustness of detection.
- Unified Attack Defense: This framework is the first that can identify replay attacks and FIDA at the same time within static state estimation.
- Precision Classification: It achieves near-perfect separation between replay events and FDIA instances.
- Meter Identification: This feature allows for the precise localization of the exact meters affected under FDIA conditions.
- System Scalability: This was validated on IEEE benchmark grids, including the 14-bus and 57-bus systems.

3.6.4 Evaluation

- Replay Attack Recognition: There is a sharp rise in Linear Eigen Value Statistics (LES) observed at the start of replay attacks, which allows for immediate detection.
- FDIA Detection: The detection accuracy remains above 94% even in noisy environments with variance up to 0.05.
- Attack Differentiation: The SVD-CNN model achieved flawless classification on the IEEE 14-bus system and over 99% accuracy when distinguishing between replay and FDIA.
- Localization Accuracy: The SVD-CNN framework significantly improved recall from 73.31% to 98.71% on the IEEE 14-bus system and from 75% to 91.67% on the IEEE 57-bus system.
- Efficiency: Both detection and localization tasks were completed in milliseconds, making this approach well-suited for real-time applications.

3.7 "Anomaly Detection in Surveillance Camera Data"

3.7.1 Introduction

The Master's thesis by Viktoriia Semerenska at Blekinge Institute of Technology (2023) looks into how machine learning can help identify unusual human activities in surveillance footage. As monitoring systems grow quickly in public and private areas, processing large amounts of video data in real time becomes a challenge. The study highlights the need for automated anomaly detection to spot potential risks.

3.7.2 Characteristics and Implementation

- Research Methodology: The study uses a mixed-methods approach that combines a Systematic Literature Review (SLR) with controlled experimental evaluation.
- Algorithms Assessed: The experimental framework tested several machine learning models, including CNN, LSTM, RNN, and SVM.
- Datasets Used: The literature review looked at well-known surveillance datasets like UCSD, UMN, Avenue, ShanghaiTech, and UCF-Crime. The experimental phase used selected datasets for practical validation.
- Performance Indicators: The study mainly used ROC-AUC and Equal Error Rate (EER) as the main measures of effectiveness.
- Experimental Setup: Each algorithm was trained and tested on pre-processed surveillance video datasets, with direct comparisons made across models.

3.7.3 Features

- Algorithm Benchmarking: Provides a comparison of various machine learning methods for detecting anomalies.
- Real-World Orientation: Focused on real-time use, especially for surveillance systems that include embedded ML hardware.
- Extensive Literature Integration: Gathers insights from more than 20 prior studies, bringing together knowledge on datasets, evaluation methods, and algorithm trade-offs.
- Collaborative Framework: Suggests using the complementary strengths of different models to achieve greater reliability.

3.7.4 Evaluation

- CNN: Delivered the strongest results with ROC-AUC=0.8346 and EER=0.2439
- LSTM: ROC-AUC = 0.7797, EER = 0.3039.
- RNN: ROC-AUC = 0.7602, EER = 0.3292.
- SVM: ROC-AUC = 0.7281, EER = 0.3780.
- Findings: CNNs consistently outperformed both sequence-based models and traditional ML methods. However, each algorithm showed unique strengths based on the type of anomaly and the specific context.

3.8 "Detection of Replay Attacks in Cyber-Physical Systems Using a Frequency-Based Signature"

3.8.1 Introduction

This paper, authored by Helem Sabina Sánchez, Damiano Rotondo, Teresa Escobet, Vicenç Puig, Jordi Saludes, and Joseba Quevedo, proposes a novel frequency-based signature method for detecting replay attacks in cyber-physical systems (CPS). Replay attacks are a trick that replaces real sensor readings with data that has been recorded before. This allows attackers to hide their harmful actions. Unlike past methods that used Gaussian Signatures or random game theory, this approach includes a time-varying sinusoidal authentication signal in a closed-loop system. It then checks if the output frequency spectrum matches the expected signature.

3.8.2 Characteristics and Implementation

- Authentication signal: A sinusoidal input with a verifying frequency is injected into the control channel to serve as a unique identifier.

- Channel Decoupling: Vector fitting is used to separate input-output pathways. This ensures that each injected signature only affects its assigned output.

- Detection Framework:

  - System outputs go through a set of band-pass filters to extract relevant frequency components.

  - The distribution of energy in these filtered signals is examined to reconstruct the expected frequency profile.

- Any difference between the reconstructed and observed profiles indicates a replay attack.
- System Model: The proposed framework was validated using a quadruple-tank process as the case study.
- Detection Principle: The reconstructed frequency profile is compared to the known authentication signal. This helps identify compromised output channels.

3.8.3 Features

- Channel Localization: It can identify which specific output channel has been targeted during a replay attack.
- Non-Intrusive Design: The injected authentication signal has a zero mean. This keeps the system dynamics unbiased.
- Versatility: It can work independently or be combined with other replay detection systems for better resilience.
- Interpretability: The frequency-based method offers clear and easy-to-understand detection logic.
- Domain Suitability: It is especially effective in CPS settings where Gaussian noise signatures don't work well because of actuator bandwidth limits.

3.8.4 Evaluation

- Case Study Application: The methodology was tested using a quadruple-tank process simulation.
- Results:
  - Replay attacks were successfully detected by spotting mismatches in reconstructed frequency profiles.
  - The system showed it could locate compromised channels.
  - It proved robust in distinguishing authentic signals from replayed ones.
- Comparative Advantage: The proposed frequency-based signature method performed better than traditional Gaussian signature techniques, especially in cases where actuator bandwidth posed challenges.

3.9 "Detecting Replay Attacks Using Multi-Channel Audio: A Neural Network-Based Method"

3.9.1 Introduction

This paper, authored by Yuan Gong, Jian Yang, and Christian Poellabauer, addresses the vulnerability of voice-controlled systems to replay attacks. While most prior research focused on single-channel audio, this work introduces a neural network-based model that leverages multi-channel audio captured by microphone arrays. The motivation is that spatial information (e.g., time difference of arrival, TDoA) is harder for attackers to manipulate than spectral or temporal features, making multi-channel approaches more robust for voice anti-spoofing.

3.9.2 Characteristics and Implementation

- End-to-End Neural Framework: Integrates beamforming, feature extraction, and classification into a single trainable neural network.

- Beamforming: Uses a filter-and-sum beamformer with learnable front-end filters to capture both spatial and spectral cues.

- Architecture:

    - Input: multi-channel audio frames (20 ms, non-overlapping).

    - Front-end filtering → convolution + pooling → fully connected layers.

    - Sequence modeling with stacked LSTM layers.

    - Final classification into genuine vs replayed.

- Dataset: Evaluated on ReMASC corpus, which includes genuine and replayed samples recorded across multiple microphone arrays (2−7 channels).

- Training: End-to-end optimization with weighted cross-entropy loss to handle class imbalance.

3.9.3 Features

- Data-Driven: No manual feature engineering; adaptable to any microphone array geometry.

- Scalable: Supports arbitrary number of channels, unlike prior two-channel methods.

- Robustness: Exploits spatial cues (TDoA, spatial correlation) that are difficult for attackers to spoof.

- Efficiency: Uses only the first 1 second of audio for classification, reducing computational overhead.

- Flexibility: Can be combined with other neural anti-spoofing models.

3.9.4 Evaluation

- Baselines: Compared against single-channel (NN-Single) and dummy multi-channel (replicated input) models.

- Results:

    - NN-Multichannel achieved up to 34.9% relative improvement in Equal Error Rate (EER) over NN-Single.

- Performance consistently improved as more microphones were added, with best results when all channels were used.

- Optimal number of front-end filters per channel was 64, balancing accuracy and training efficiency.

- Limiting analysis to the initial one-second audio segment provied the most effective balance between recognition accuracy and processing speed.

- Key findings: The observed improvements were attributed to the effective use of genuine spatial features rather than simply expanding the number of model parameters.

CHAPTER 4

PROJECT REQUIREMENTS SPECIFICATION

4.1 Functional Requirements

These describe the core features your system must provide. For your project, examples could be:

- The system must capture video streams from RTSP sources or file inputs without delays.
- Incoming frames need to be normalized, have their optical flow computed, and undergo SDR encoding to prepare the data for analysis.
- An HTM model will be trained using clean video sequences to establish baseline behavior.
- This trained HTM model will be applied to live video streams to identify unusual activity in real time.
- Each frame must be hashed using secure algorithms like SHA-256 or BLAKE-2 to ensure its integrity.
- Incoming frames will be checked against stored hashes to spot replay attacks or altered inputs.
- The system must generate alerts and keep logs whenever it detects replay evidence or anomalies.
- A dashboard or console output should be available to let administrators monitor system activity and detection results.

4.2 Non-Functional Requirements

- Performance : The system must be capable of processing video stream at a minimum of X frames per second to ensure real-time operation.

- Scalability: The architecture should support concurrent handling of multiple video streams without degradation in performance.

- Security: All stored frame hashes and metadata must be protected against tampering, ensuring data integrity and authenticity.

- Reliability: The detection framework shall consistently achieve at least 95% accuracy in identifying replay attacks under varying conditions.

- Usability: Generated alerts must be clear, human-readable, and accessible through a straightforward interface for administrators.

- Maintainability: The system shall be modular, allowing independent updates to pre-processing , detection, and verification modules.

- Portability: The system shall run on Linux/Windows environments with minimal configuration.

4.3 System Constraints

- The anomaly detection component will use HTM.
- Secure cryptographic hashing algorithms like SHA-256 must be used to validate frame authenticity.
- A lightweight SQLite database will be used to store frame hashes and related metadata.

CHAPTER 5

SYSTEM DESIGN

As shown in Fig 5.1, the system architecture for replay attack detection in CCTV streams is organized into a modular pipeline that ensures efficient video processing, anomaly detection, and alert generation. The workflow begins with the Video Source, which can be either stored video files or live RTSP streams. These inputs are passed into the Core Processing module, where the video is ingested, preprocessed, and converted into Sparse Distributed Representations (SDRs) for further analysis. This module also supports visualization and HTM training to learn normal motion patterns.

To evaluate the system's robustness, an Attack Simulation module is included, allowing replay attacks to be injected into the stream for testing purposes. The Model and Data component supports both training and inference, enabling the system to adapt to new patterns and maintain historical context.

The Live Detection module performs HTM inference on incoming SDRs and uses a Decision Engine to interpret anomaly scores and hash comparisons. This engine determines whether frames are clean or suspicious and triggers appropriate responses such as alerts, dashboard updates, or frame hashing for forensic verification. Finally, the System Administrator interacts with the dashboard to monitor alerts and system status, ensuring operational oversight and response coordination.

This architecture supports scalable, modular deployment and provides a comprehensive framework for detecting replay attacks in surveillance environments.

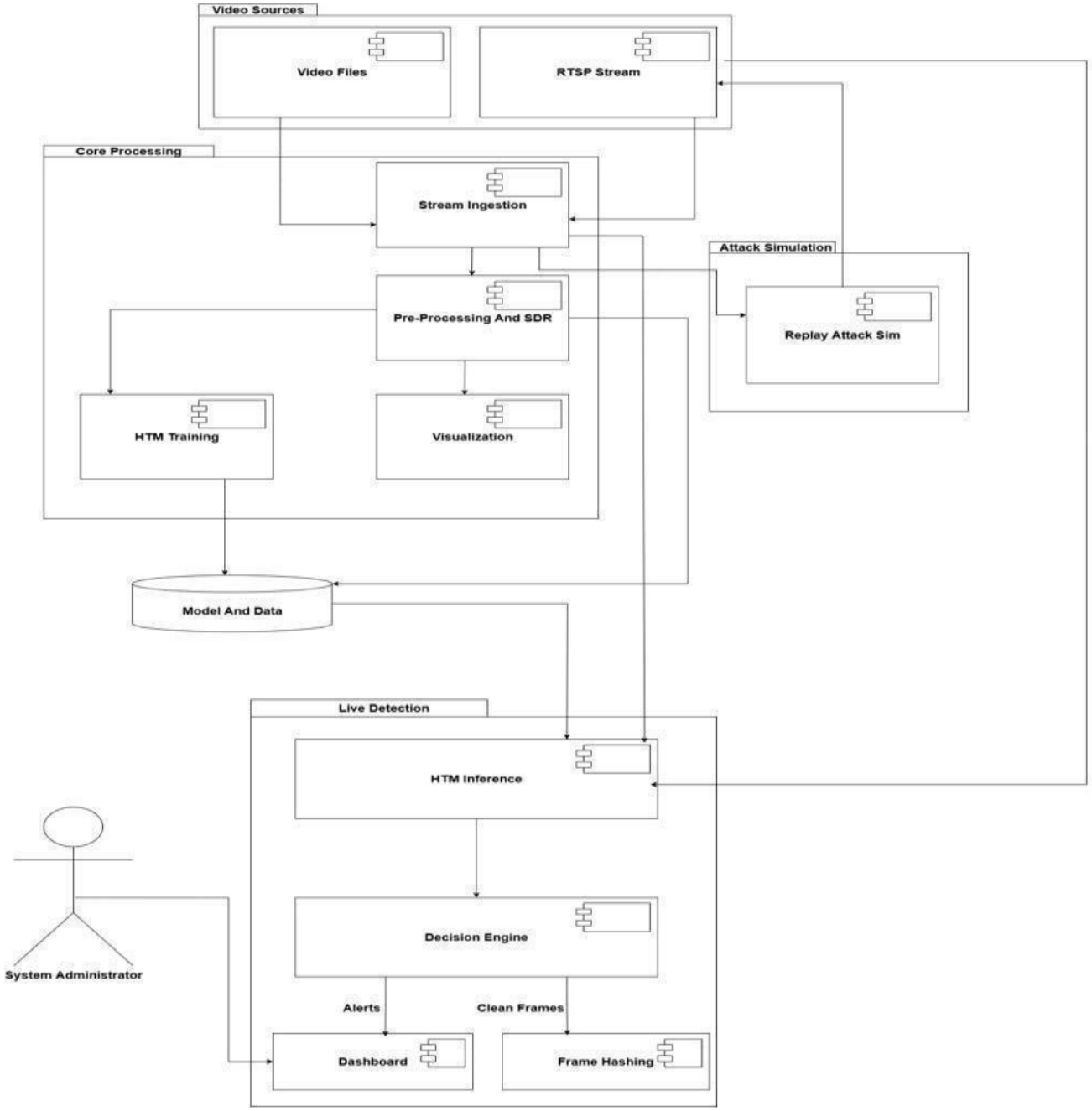

Fig 5.1 System Design

CHAPTER 6

PROPOSED METHODOLOGY

The proposed framework merges HTM for detecting anomalies with cryptographic verification. This creates a strong method for spotting replay attacks in video surveillance settings. The design consists of two main phases: Training and Live detection, supported by a verification and alerting pipeline.

6.1 Training Phase

- Data Acquisition: Video streams are collected from surveillance cameras and cleaned.
- Pre-Processing: Each frame is normalized. Motion features are extracted using optical flow and are then encoded into SDR to capture spatio-temporal dynamics.
- HTM Model Training: The HTM network trains exclusively on footage without attacks. This allows it to learn the normal behavior patterns.
- Model Repository: Trained models are stored in a central repository to ensure they are available for future use during live monitoring.

6.2 Live Detection Phase

- Stream Capture: Real-time video streams are continuously gathered from surveillance cameras.
- Frame Pre-Processing: Incoming frames go through the same normalization and SDR encoding pipeline used in the training phase to keep consistency.
- HTM Interface: The trained HTM model examines live frames and produces anomaly scores that show deviations from learned normal behavior.
- Decision Engine:

- When the HTM generates anomaly scores that exceed a set threshold, the system flags the input as possibly compromised.

- Clean frames are sent to the verification stage for integrity checks.

6.3 Verification Pipeline

- Frame Normalization: Suspected frames are standardized to ensure consistency before hashing.
- Cryptographic Hashing: Each frame gets converted into a secure digital fingerprint using algorithms like SHA-256.
- Database Storage: Hash values and metadata are stored in a lightweight SQLite database.
- Verification Module:
  - New hashes are compared against previously stored clean references.
  - If identical hashes are found across different time intervals, the system confirms a replay.
  - If no match is found, the frames are saved as part of the clean reference dataset.

6.4 Alerting and Logging

- Alert Generation: After confirming replay evidence, the system sends real-time alerts to the monitoring dashboard for immediate action by administrators.
- Event Logging: All detection events are logged with detailed metadata, including timestamp, camera ID, anomaly score, and hash evidence.
- Administrator Interface: Security personnel can review alerts, replay evidence, and view system logs.

6.5 Advantages of the Methodology

- Dual Defense: This approach combines machine learning (HTM) for spotting anomalies with cryptographic verification for confirming replay evidence.
- Noise Tolerance: HTM's online learning adapts to environmental changes, reducing false positives.
- Explainability: Grid-based anomaly scores and hash evidence provide clear results.
- Lightweight Deployment: SQLite and modular pipelines ensure portability and scalability.

CHAPTER 7

IMPLEMENTATION AND PSEUDOCODE

7.1 Stream Ingestion

Implementation:

- Uses OpenCV to capture frames from RTSP streams or video files.
- Keeps frame timestamps for later verification

```
Algorithm Stream_Ingestion(video_source):
    Input: RTSP stream or video file
    Output: Sequence of frames with timestamps

    cap ← OpenVideo(video_source)
    while cap.isOpened():
        frame, timestamp ← cap.read()
        if frame is not None:
            yield (frame, timestamp)
        else:
             break
     cap.release()
```

7.2 Pre-Processing and SDR Encoding

Implementation:

- Frames are resized and normalized.
- Optical flow is computed to capture motion.

- Features are encoded into Sparse Distributed Representations (SDRs).

```
Algorithm Preprocess_Frame(frame):
    Input: Raw video frame
    Output: SDR encoding

    resized ← Resize(frame, target_size)
    normalized ← Normalize(resized)
    flow ← ComputeOpticalFlow(normalized)
    sdr ← EncodeToSDR(flow)
    return sdr
```

7.3 HTM Training

Implementation:

- HTM model is trained on clean, attack-free footage.
- Learns normal temporal patterns of motion.

```
Algorithm Train_HTM(clean_video):
    Input: Clean video frames
    Output: Trained HTM model

    HTM ← InitializeModel()
    for frame in Stream_Ingestion(clean_video):
        sdr ← Preprocess_Frame(frame)
        HTM.Train(sdr)
    SaveModel(HTM, "ModelRepository")
```

7.4 HTM Inference (Live Detection)

Implementation:

- Loads trained HTM model.

- Computes anomaly scores for each incoming frame.

```
Algorithm HTM_Inference(live_stream):
    Input: Live video stream
    Output: Anomaly scores

    HTM ← LoadModel("ModelRepository")
    for frame in Stream_Ingestion(live_stream):
        sdr ← Preprocess_Frame(frame)
        score ← HTM.Infer(sdr)
        yield (frame, score)
```

7.5 Decision Engine

Implementation:

- Compares anomaly score against threshold.

- Suspicious frames are forwarded to verification.

```
Algorithm Decision_Engine(frame, score, threshold):
    if score > threshold:
        result ← Verify_Frame(frame)
        if result = "Replay Detected":
            GenerateAlert(frame, score)
            LogEvent(frame, score, "Replay Evidence")
        else:
            StoreCleanFrame(frame)
    else:
        StoreCleanFrame(frame)
```

7.6 Verification Module

Implementation:

- Normalizes frames.
- Computes cryptographic hash (SHA-256 / BLAKE2).
- Compares with stored hashes in SQLite DB.

```
Algorithm Verify_Frame(frame):
    normalized ← Normalize(frame)
    hash_value ← ComputeHash(normalized, "SHA-256")
    metadata ← {timestamp, camera_id}

    if DB.Contains(hash_value):
        return "Replay Detected"
    else:
        DB.Insert(hash_value, metadata)
        return "Clean Frame"
```

7.7 Cryptographic Hashing and Database

Implementation:

- Uses Python's hashlib for SHA-256/BLAKE2.
- Stores hash + metadata in SQLite DB.

```
Algorithm ComputeHash(frame, algorithm):
    if algorithm = "SHA-256":
        return SHA256(frame.bytes)
```

```
    else if algorithm = "BLAKE2":
        return BLAKE2(frame.bytes)
```

7.8 Alerting and Logging

Implementation:

- Alerts are pushed to a dashboard or console.
- Logs are stored with metadata for forensic analysis.

```
Algorithm GenerateAlert(frame, score):
    Display("ALERT: Replay Attack Detected")
    Display("Anomaly Score:", score)
    Display("Timestamp:", frame.timestamp)

Algorithm LogEvent(frame, score, status):
    log_entry ← {timestamp, camera_id, score, status}
    WriteToLogFile(log_entry)
```

CHAPTER 8
RESULTS AND DISCUSSION

As shown in Fig 8.1, the inference results for normal CCTV footage demonstrate the baseline behavior of the anomaly detection system in the absence of replay attacks. A total of 442 frames were processed during this evaluation. The average anomaly score recorded was 0.4742, indicating that the motion patterns observed were generally consistent with the learned temporal sequences. The maximum anomaly score reached 0.9750, which may correspond to brief irregularities such as sudden motion or environmental changes, but these were not sustained. Only one alert was triggered throughout the entire sequence, resulting in an alert rate of just 0.2%. This low alert frequency confirms that the system maintains high stability and precision when analyzing clean footage, effectively minimizing false positives and ensuring that alerts are only raised for significant deviations. These results validate the reliability of the HTM-based detection framework under normal operating conditions.

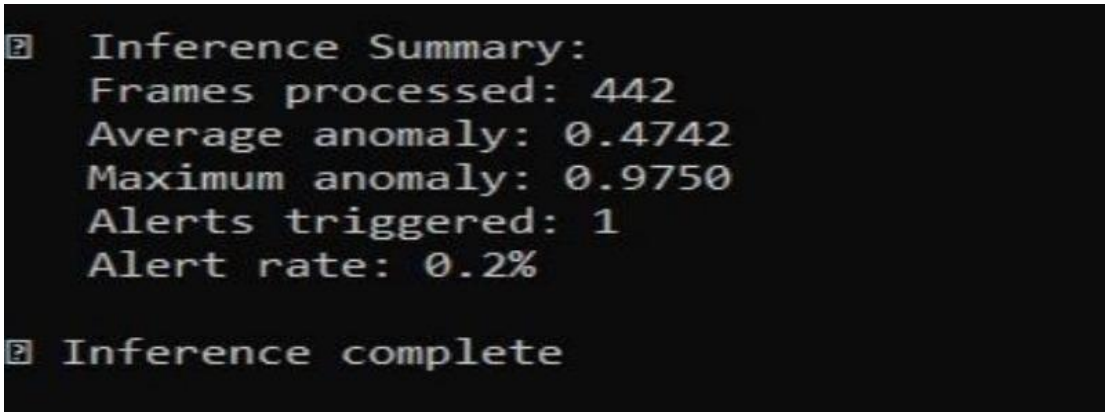

Fig 8.1 Inference for Normal Footages

As shown in Fig 8.2, the system was evaluated on a video sequence containing simulated replay attacks to test its ability to detect anomalous behavior. A total of 479 frames were processed during this inference cycle. The average anomaly score was 0.3590, which is lower than the baseline for normal footage, indicating that the replayed segments were significantly different from the learned motion patterns. The maximum anomaly score reached 1.0000, reflecting a strong deviation during the replay intervals. A total of 161 alerts were triggered, resulting in an alert rate of 33.6%, which is well above the defined threshold of 10% used to flag replay attacks.

Based on this high alert frequency, the system successfully identified the presence of a replay attack. These results demonstrate the effectiveness of the HTM-based anomaly detection combined with frame-level hashing in distinguishing replay.

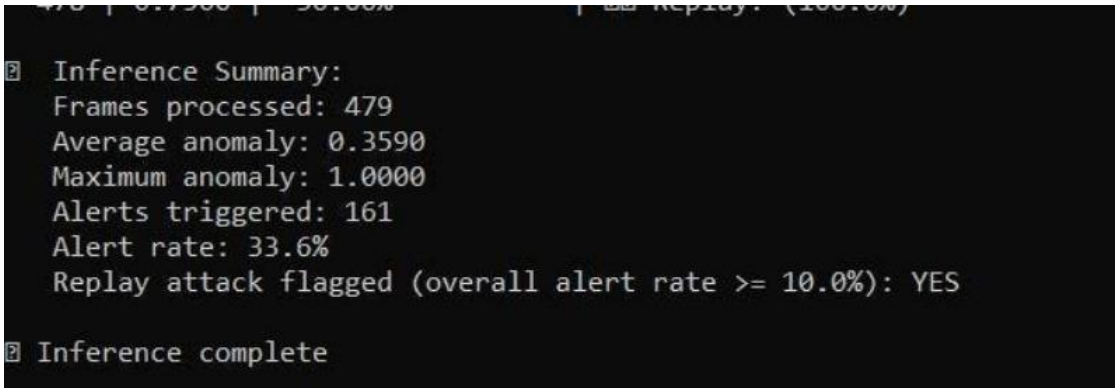

Fig 8.2 Inferences for Replayed Footage

As shown in Fig 8.3, the training log illustrates the learning progression of the Hierarchical Temporal Memory (HTM) model across 15 epochs. The graph plots the average anomaly score over time, revealing a consistent downward trend. Initially, the anomaly values are relatively high, indicating that the model is unfamiliar with the motion patterns in the input data. However, as training progresses, the average anomaly score steadily decreases, demonstrating that the HTM model is successfully learning and adapting to the temporal structure of the video stream. By the final epoch, the anomaly score stabilizes below 0.2, suggesting that the model has effectively internalized the normal behavior and is well-prepared for inference tasks. This training behavior confirms the suitability of HTM for unsupervised learning in surveillance applications, where temporal consistency is key to detecting anomalies such as replay attacks.

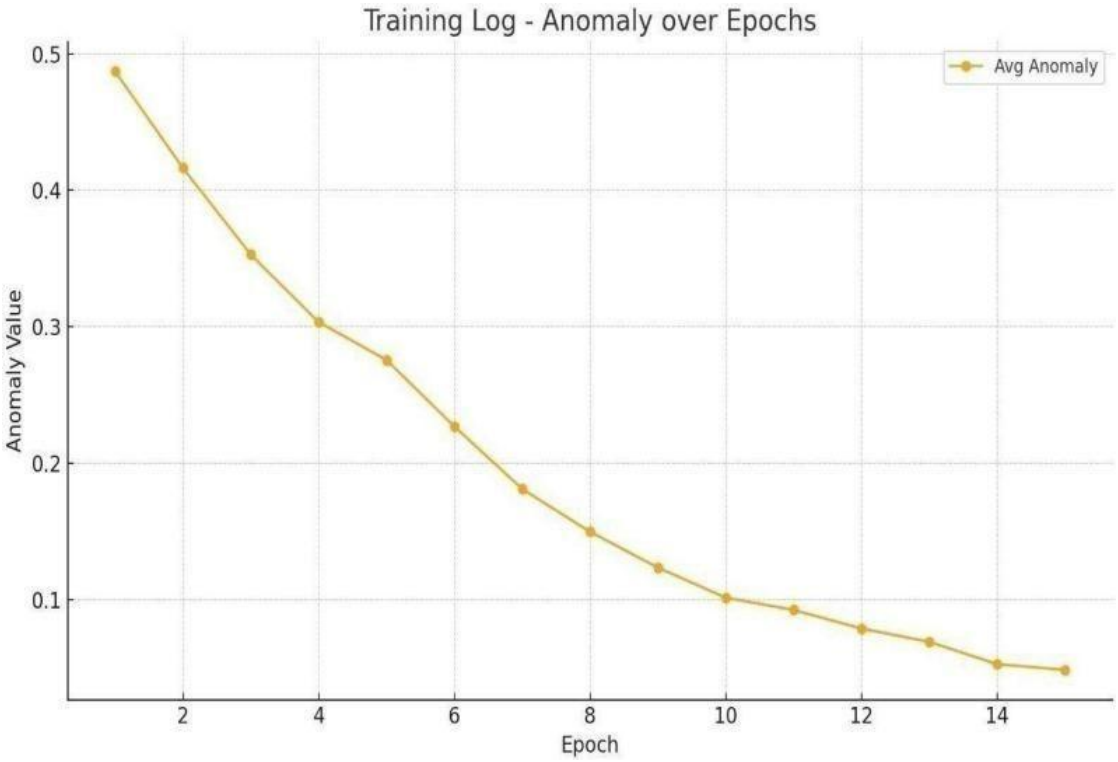

Fig 8.3 HTM Traning Results

8.3 Discussions

Effectiveness of Dual Approach:

- HTM alone was effective in flagging anomalies but prone to false positives.
- The cryptographic verification module eliminated ambiguity by confirming replay evidence.
- Together, the system provided both early anomaly detection and forensic proof of replay.

Comparison with Literature:

- Unlike deep learning-based methods (e.g., CNN/LSTM), HTM required no large training dataset and adapted online.
- Compared to frequency-based or random matrix approaches, the proposed method offered lighter computation and real-time feasibility.

Limitations Observed:

- Performance degraded slightly under moving camera scenarios, since HTM assumes stationary viewpoints.
- Sudden environmental changes (e.g., abrupt lighting shifts) occasionally triggered false alarms.
- Database size grows with long-term storage; periodic pruning or rolling windows are needed.
- Strengths:

- Explainability: HTM anomaly scores and hash matches provide clear evidence.
- Scalability: The modular design allows deployment on multiple cameras.
- Security: Cryptographic hashing ensures tamper-proof replay detection.

CHAPTER 9

CONCLUSION AND FUTURE WORK

- Created a strong video surveillance system to spot replay attacks and verify frame integrity.
- Extracted motion dynamics using Farneback optical flow and encoded them into Sparse Distributed Representations (SDRs) for HTM
- HTM model learned normal temporal patterns and flagged anomalies in real time.
- Simulated replay attacks with looped pre- crime footage to validate resilience.
- Integrated frame hashing and database verification to provide tamper- evident audit trails.
- Combined anomaly detection with cryptographic verification, delivering a dual defense system that is both technically sound and practical for real- world deployment.

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APPENDIX A DEFINITIONS, ACRONYMS AND ABBREVIATIONS

DEFINITIONS

1. Replay Attack: It is a type of cyber-attack where a malicious actor captures valid video frames and then streams to deceive surveillance systems.

2. Optical Flow: It is a technique to analyse motion patterns between consecutive video frames by detecting any pixel displacement

3. Hierarchical Temporal Memory: It is a machine learning approach which is inspired by the human neo-cortex which is mainly used for anomaly detection in sequential data.

4. RTSP (Real Time Streaming Protocol): It is a network protocol which is used for controlling streaming media servers, commonly used in CCTV surveillance.

5. SHA-256 Hashing: It is a cryptographic hash function which is used to verify frame integrity and detect any sort of tampering in video streams.

6. FFMpeg: It is a multimedia framework which is used for handling video processing, encoding and streaming.

7. Farneback Optical Flow: And advance method which is used for computing dense motion vectors between frames thus enhancing anomaly detection capabilities.

8. MediaMTX: It is a lightweight RTSP server which is used for managing and simulating video streaming environments in surveillance projects.

ACRONYMS AND ABBREVIATIONS

1. AI (Artificial Intelligence)
2. CCTV (Closed Circuit Television)
3. RTSP (Real Time Streaming Protocol)
4. FFMpeg (Fast Forward Moving Picture Experts group)
5. HTM (Hierarchical Temporal Memory)
6. MIL (Multiple Instance Learning)
7. SHA-256 (Security Hashed Algorithm 256)
8. CVPR (Conference on Computer Vision and pattern recognition)
9. FPS (Frames Per Second)
10. BGR (Blue Green Red)
11. HSV (Hue Saturation Value)