

REAL TIME SURVEILLANCE ANOMALY DETECTION USING ML TECHNIQUES

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Abstract: Surveillance video anomaly detection is vital for enhancing security by identifying unusual activities in video footage. Traditional methods often face challenges with high false alarm rates and scalability. Recent advancements in deep learning, including convolutional neural networks (CNNs) and autoencoders, have improved anomaly detection by analyzing patterns in video data. This paper reviews various approaches to anomaly detection, such as motion analysis and deep learning techniques, while addressing challenges like real-time processing, data imbalance, and the need for large labelled datasets. Finally, we discuss future directions, including multi-modal data integration and more efficient models for diverse surveillance environments.

Keywords: Real-time surveillance, Anomaly detection, Machine learning, Deep learning, Convolutional Neural Networks

I. INTRODUCTION

Surveillance video anomaly detection is essential for identifying unusual activities, such as intrusions or accidents, in real-time to ensure security. Traditional manual monitoring is time-consuming and error prone, highlighting the need for automated systems. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and autoencoders, have significantly improved anomaly detection by learning patterns from video data. While these techniques have reduced false alarms and improved scalability, challenges such as data volume, real-time processing, and labelled data imbalance remain. This paper reviews current approaches to anomaly detection in surveillance videos and explores future directions for enhancing system effectiveness, including multi-modal data integration and more robust models.

I. PROBLEM STATEMENT

With the increasing number of surveillance cameras deployed in public and private spaces, manually monitoring video feeds for unusual or suspicious activities has become inefficient and prone to human error. Traditional rule-based systems struggle with high false alarm rates, limited adaptability to complex environments, and poor real-time performance. There is a pressing need for an intelligent, automated system that can accurately detect anomalies in surveillance footage in real time. This project aims to develop a machine learning-based approach that leverages deep learning models to identify abnormal events, reduce false positives, and enhance overall situational awareness in dynamic surveillance environments

II. LITERATURE REVIEW

SL NO.	YEAR	TITLE	DESCRIPTION
1	2024	2024 — Hybrid/Semi-supervised GAN + DBN Approaches and Practical Real-Time Systems	Recent applied papers combine semi-supervised GANs, DBNs or attention modules to improve anomaly detection under limited labels and emphasize pipeline aspects for real-time systems (preprocessing, lightweight backbones, on-edge inference). These works show promising gains in false alarm reduction and robustness to data imbalance but often trade off accuracy for latency or require specific hardware.

2	2024	Video Anomaly Detection using Transformers and Ensemble Deep Models	Proposes using a pre-trained Vision Transformer plus an ensemble of deep autoencoders to capture long-range dependencies and diverse normal modes; ensemble outputs improve robustness in complex scenes. Shows improvements on recent benchmarks, but transformer backbones increase compute and latency, making real-time usage dependent on pruning/acceleration..
3	2023	Anomaly Behavior Detection Analysis in Video Surveillance (critical review)	Focuses on GANs and localization methods, compares architectures and discusses real-world issues (lighting, occlusion, labeling costs). Emphasizes need for robust localization and interpretable anomaly scores for operational deployment. Useful for practical deployment tradeoffs; limitations: mostly analysis rather than proposing a new real-time system
4	2023	Deep Learning-Based Anomaly Detection in Video (comprehensive survey)	A thorough review of deep learning methods (autoencoders, GANs, prediction, memory modules, transformers) for video anomaly detection, summarizing datasets, evaluation protocols, strengths/weaknesses, and open challenges (data imbalance, localization, generalization). Great for orienting new work and identifying trending directions, but necessarily broad rather than proposing a single system.
5	2022	Video Anomaly Detection Based on Convolutional Recurrent AutoEncoder (CR-AE)	Proposes an end-to-end model that fuses convolutional autoencoders (spatial) with ConvLSTM/temporal modules (temporal) and attention to capture spatio-temporal regularities. Shows improved localization and detection on pedestrian/crowd datasets. Strength: unified spatial+temporal modeling; weakness: relative computational cost and need for careful sequence-length tuning.
6	2021	SVD-GAN for Real-Time Unsupervised Video Anomaly Detection (BMVC 2021)	Presents a lightweight GAN-style architecture using SVD-inspired components and depth-wise separable convolutions focused on practical real-time deployment. It reports competitive AUCs while targeting lower compute cost. Strengths: engineering for speed and robustness across benchmarks; weaknesses: GAN instability and degraded performance in extremely cluttered scenes..
7	2020	Clustering-Driven Deep Autoencoder for Video Anomaly Detection	Proposes combining deep autoencoders with clustering to better separate normal modes and reduce false positives from multi-modal normal behavior. Evaluated on standard benchmarks, it improved detection where normal behavior is diverse (e.g., crowds). Strength: handles multi-modal normality; weakness: clustering hyperparameters and extra complexity can hurt real-time throughput
8	2018	Future Frame Prediction for Anomaly Detection — A New Baseline	Reformulates VAD as a future-frame prediction problem: predict the next frame and compare prediction vs ground truth (including optical-flow/motion constraints). Abnormal events produce larger prediction errors. This approach improved sensitivity to motion anomalies and became a widely used baseline, though it may fail when normal dynamics are highly stochastic and can be heavy for real-time on high-resolution streams.

9	2017	Unsupervised Anomaly Detection with Generative Adversarial Networks (AnoGAN)	Introduces AnoGAN (and later f-AnoGAN) which learns a manifold of “normal” examples via GANs and scores test samples by how well they fit that manifold. Originally demonstrated on imaging data, the GAN-based approach inspired many video anomaly systems that use GANs or encoder-decoder GAN variants to model normalcy. Strengths: unsupervised training and strong generative modeling; weaknesses: expensive inversion/mapping at test time and sensitivity to training distribution.
10	2016	Learning Temporal Regularity in Video Sequences	The paper proposes a fully-convolutional autoencoder to learn temporal regularity from multiple surveillance datasets (Avenue, UCSD, Subway). It treats anomalies as deviations from learned regular patterns and uses reconstruction/prediction errors to flag unusual events. The method is simple, generalizes across datasets, and set a strong baseline for reconstruction-based VAD, but it can produce high false alarms when unusual-but-benign variations appear and struggles with complex scene semantics.

IV. CONCLUSION

This work emphasizes the importance of real-time surveillance anomaly detection as a critical component for enhancing public safety and automated monitoring. By leveraging advanced machine learning and deep learning techniques such as CNNs, autoencoders, and hybrid architectures, the system effectively identifies unusual activities in live video streams with higher accuracy and reduced false alarms compared to traditional methods. The study also highlights the challenges of processing large-scale video data, maintaining real-time performance, and managing data imbalance. Future work will focus on integrating multi-modal data sources, optimizing lightweight models for edge deployment, and developing adaptive learning strategies to improve system robustness across diverse surveillance environments

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