"A Survey on Outlier Detection in Videos Using Machine Learning Methods: Embracing New Trends and Technologies"

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AbstractThe applications of anomaly detection in videos of behavior analysis, security, and surveillance have made this field of study important. A thorough analysis of machine learning methods for anomaly detection in video data is given in this survey. We group the techniques into three categories: semi-supervised, supervised, and unsupervised learning approaches. We describe the benefits, drawbacks, and methods of each category. In addition, we go over frequently utilized datasets and assessment criteria, as well as problems and potential future study areas in the area.

Keywords: Anomaly detection, Datasets, scalability, Quality, Efficiency

1.1. Introduction

Detecting anomalies in videos entails spotting odd occurrences or behaviors that don't fit the pattern. The dynamic nature of the video data, the multifaceted nature of some anomalies, and the need for real-time detection make this work challenging. Reviewing current machine learning methods used to solve this issue and provide analysis on their effectiveness and relevance are the goals of this survey.

2. Categories of Machine Learning Techniques

2 Supervised Learning

In a supervised learning, model is trained on labeled dataset. While these methods are very powerful, they rely strongly on the availability of annotated data.

2.1.1 Classification-Based Approaches

Support Vector Machines (SVMs): SVMs are mainly used by defining a hyper plane that separates the classes for detecting normal or abnormal events.

Convolutional Neural Networks (CNNs) – make sure to use these for more complex scenes, where anomalies have multiple layers of properties.

2.1.2 Regression-Based Approaches

Linear Regression: These simple models can sometimes be used to predict normal behavior and help identify when things are not like them.

- Neural Network Regression Models: State of the art models that can capture nuanced patterns in video data from anomaly detections.

2.2 Unsupervised Learning

- These algorithms are rarely used, as they do not need to have any labeled data. This makes them decent for settings where you do not know in advance what normality really looks like but generally even there these methods still underperorm managed baselines.
- In , a simple TCP friendly transmission control mechanism is used by the sender to avoid burst transmissions, where as in more recent multiplayer games like Halo Reach and Battlefield 3 where too many users are associated with end choke point i.e. server which leads to serving of large data packets resulting in much unicast load on game servers, event based adaptation should be utilized which overhears all explicit events from global network module related to signaling process or avoiding out-of-order arrival using time-out mechanisms as described above abruptly with respect synchronization process without considering any models or heuristics to decide between stability and timeliness constraints given an idealized gaming scenario such multi-user interactions occur only rarity (fallout shelters)[20].
- K-Means Clustering: It groups together the data points that are more similar among them (and have max between 2 clusters) and cut the outliers with are not well situated in a certain cluster.
- DBSCAN (Density-Based Spatial Clustering of Applications with Noise): Finds core samples of high density and expands clusters from them.

2.2.2 Reconstruction-Based Approaches

Reconstruction-Based Approach The second fundamentally different approach is using a reconstruction signal.

Auto encoders – Neural networks that learn to reconstruct their input data. A high reconstruction error means that it is an anomaly.

GAN — Generative Adversarial Networks (discriminator/generator) The discriminator which learns to distinguish between the real and generated data is what will detect anomalies.

2.3 Semi-Supervised Learning

Semi-supervised learning involves leveraging a combination of a small set of labeled data and a large set of unlabeled data.

2.3.1 Hybrid Models

- **Self-Training Algorithms:** These algorithms are initially trained on labeled data and subsequently retrained iteratively using their own most confident predictions.
- **Co-Training Models:** Co-training models make use of multiple perspectives of the data to enhance learning accuracy and detect anomalies.

3. Literature Survey

In recent years, the field of video anomaly detection has garnered significant attention due to its critical applications in surveillance, public safety, and security systems. The ability to automatically identify abnormal events in video footage is essential for timely and effective response to potential threats. This literature review aims to provide a comprehensive overview of the state-of-the-art advancements in video anomaly detection, highlighting the innovative methodologies, datasets, and ongoing challenges faced by researchers in this domain.

Table 2.1 Literature review

PAPER	INSIGHTS	METHODS USED	DATASETS	LIMITATIONS
Waseem Ullah et.al (2021)	• Efficient anomaly recognition using attention residual LSTM in surveillance videos. • Outperforms state-of-the-art models with increased accuracy on benchmark datasets	○ Efficient light-weight CNN-based anomaly recognition framework ○ Residual attention-based LSTM network for precise anomaly detection and recognition	○ UCF-Crime dataset ○ UMN and Avenue datasets	○ Deep learning models lack generalization abilities and have high time complexity. ○ Anomaly recognition in surveillance videos is challenging due to infrequent occurrences.
Boyang Wan et.al (2021)	○ Large-scale Anomaly Detection (LAD) database with 2000 video sequences ○ Multi-task deep neural network outperforms state-of-the-art methods.	○ Multi-task deep neural network ○ Inflated 3D convolutional (I3D) network	○ Large-scale Anomaly Detection (LAD) database with 2000 video sequences. ○ Contains 14 anomaly categories including crash, fire, violence, etc..	○ Existing anomaly databases limited in scale. ○ Lack precise time duration annotations for abnormal events.

PAPER	INSIGHTS	METHODS USED	DATASETS	LIMITATIONS
Jiangfan Feng et. Al (2021)	○ Two-stream autoencoder for efficient anomaly detection in videos . ○ Post hoc interpretability through feature map visualization for model explanation.	○ Two-stream autoencoder for anomaly detection in videos. ○ Post hoc interpretability through feature map visualization for model explanation.	○ Avenue, UCSD Ped2, Subway Exit, Subway Entrance datasets used. ○ Subway videos limited to first 5-15 minutes for training	○ Uncertain and ambiguous decision boundaries in video sequences. ○ Only visualized heat map of the first convolutional layer shown.
Wang et al. (2022)	○ Multiple probabilistic models inference used for anomaly detection in videos. ○ Real-time algorithm MPI-VAD combines advantages of probabilistic models.	○ Multiple probabilistic models inference ○ Variable-sized cell structure and compact feature set extraction	○ Three publicly available datasets used for experiment results. ○ Datasets used to evaluate proposed MPI-VAD algorithm.	○ Lack of video anomaly detection methods suitable for real-time processing ○ Trade-off between detection accuracy and computational complexity not given much attention
AbdelhafidBerroukham et al. (2023)	○ Deep learning-based methods offer effective anomaly detection in videos. ○ Approaches include reconstruction error, future frame prediction, classifiers, and scoring.	○ Reconstruction error Future frame prediction Classifiers ○ Scoring	○ 1,900 lengthy surveillance movies with 13 realistic abnormalities ○ UCF dataset with examples of anomalies, more challenging than others	○ The majority of approaches require a labeled dataset with normal events. ○ This restricts continuous retraining without human intervention.

PAPER	INSIGHTS	METHODS USED	DATASETS	LIMITATIONS
Xiaosha Qi et al. (2023)	○ Dual-generator GAN method learns anomaly distribution for video anomaly detection. ○ Second-order channel attention module enhances model's learning capacity	○ Dual-generator generative adversarial network method. ○ Integration of a second-order channel attention module	○ Training data only includes normal events. ○ Difficulty for models to learn abnormal patterns.	○ Experiments conducted on two popular datasets. ○ Demonstrated superiority of proposed method in anomaly detection.
Peng Zhang et al. (2023)	○ Regression-based method suitable for large-scale video anomaly detection. ○ Feature extraction crucial for efficient anomaly detection in videos.	○ Three-dimensional multi-branch convolutional fusion network (Branch-Fusion Net) ○ Channel Spatial Attention Module (CSAM)	○ UCF-Crimes: 1900 videos, 14 behavior categories, 128 hours. ○ Crimes-mini: 5 categories, preprocessing operations, 6:2:2 ratio split.	○ Poor generalization ability and high parameter overhead in existing methods . ○ Normal video frames can be unpredictable, affecting anomaly detection accuracy.
Qianqian Zhang et al. (2023)	○ Video anomaly detection based on AE with attention mechanism. ○ Model improves feature representation and detection accuracy in real scenarios.	○ Video anomaly detection based on Auto-Encoder (AE) model ○ Introduction of attention mechanism and deep separable convolution operation	○ UCSD Ped1, UCSD Ped2, CUHK Avenue ○ Experimented datasets for video anomaly detection in the research.	○ Complex model reduces detection efficiency and accuracy. ○ Unnecessary background information affects the detection accuracy of the model.

PAPER	INSIGHTS	METHODS USED	DATASETS	LIMITATIONS
Sareer Ul Amin et al.	• Efficient Attention-based deep-learning approach for anomaly detection in videos. • Utilizes Light-weight CNN, LSTM cells, and Attention Network for detection.	○ Shots boundary detection technique for segmenting prominent frames ○ Light-weight Convolution Neural Network (LWCNN) model for extracting spatial and temporal information ○ Long Short-Term Memory (LSTM) cells and Attention Network for learning spatial and temporal features ○ Chronologically sorted frames for detecting motion and action ○ Trained ADSV model for identifying anomaly activity in the video	○ Complex and challenging benchmark datasets used for experiments ○ Comparison with state-of-the-art methodologies shows significant improvement	○ Manual search for anomalies in massive video records is difficult. ○ Anomalous events occur infrequently with low probability in real-world systems.

4. Current State of Anomaly Detection in Videos

Currently, supervised learning, unsupervised learning, and deep learning techniques are used in the field of machine learning for anomaly identification in videos. Using labeled data, supervised learning models are developed, enabling the machine to discern between typical and anomalous behavior in films. Conversely, unsupervised learning techniques can detect abnormalities in the films based on departures from the typical patterns and do not require labeled data. By identifying intricate spatiotemporal correlations, deep learning methods like recurrent and convolutional neural networks have also demonstrated potential in the detection of anomalies in videos.

5. Advancements in Anomaly Detection Techniques

The incorporation of temporal information, modeling long-range dependencies, and handling noisy or missing video data have been the main areas of recent improvement in anomaly detection techniques. To capture temporal dynamics and enhance the identification of anomalies in films, methods like temporal convolutional networks and attention mechanisms have been devised. In addition, scholars have investigated transfer learning strategies to utilize pre-trained models on extensive video datasets, permitting the modification of models for certain anomaly detection assignments with restricted annotated data.

6. Challenges and Opportunities for Future Research

Despite the progress in anomaly detection in videos, several challenges persist, including the need for large-scale annotated video datasets, interpretability of deep learning models, and generalization to diverse real-world scenarios. Future research in this area can focus on developing novel architectures that can effectively handle multimodal data and dynamic scenes. Additionally, the integration of semantic information and domain knowledge into anomaly detection systems could enhance their interpretability and enable contextual reasoning for more accurate anomaly identification.

7. Conclusion

This comprehensive literature review highlights the significant advancements and ongoing challenges in the field of video anomaly detection. Researchers have made considerable progress in developing innovative models and methodologies, such as attention-based networks, deep neural networks, auto encoders, and generative adversarial networks, which have shown promising results in improving the accuracy and efficiency of anomaly detection.

However, despite these advancements, several critical challenges remain. The issues of generalization, high computational complexity, and the infrequent occurrence of anomalies in real-world scenarios pose significant hurdles. Additionally, the need for precise time annotations, high-quality datasets, and the ability to handle diverse and unseen environments are persistent gaps that need to be addressed.

8. Future Research Directions

To further advance the field and address these challenges, the following research directions are recommended:

Enhanced Generalization and Scalability:

Focus on developing models that can generalize across different environments and reduce computational complexity for better scalability.

Improved Annotation and Dataset Quality:

Expand and refine datasets with accurate time annotations and a broader range of anomaly categories, ensuring they more accurately reflect real-world scenarios.

Longitudinal and Cross-Cultural Studies:

Conduct longitudinal studies to understand the temporal dynamics of anomalies and incorporate cross-cultural research to account for cultural nuances in detection.

Integration of Advanced Methodologies:

Embrace mixed-method approaches that combine deep learning with probabilistic models and attention mechanisms. Explore innovative techniques like reinforcement learning to enhance detection accuracy.

Real-time Processing and Efficiency:

Develop real-time anomaly detection methods that balance accuracy with computational efficiency, prioritizing lightweight models suitable for practical deployment in surveillance systems.

Interdisciplinary Collaboration and Practical Implications:

Foster interdisciplinary collaboration to integrate perspectives from various fields and translate research findings into practical applications, aiding policy development and improving public safety.

By following these research directions, the field can overcome current limitations, enhance the robustness and efficiency of anomaly detection models, and significantly contribute to practical applications in real-world settings.

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