Supplement to
"Networking Systems for Video Anomaly Detection: A Tutorial and Survey"

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This is supplementary material to our tutorial paper submitted to the ACM CSUR entitled *"Networking Systems for Video Anomaly Detection: A Tutorial and Survey"* for readers with specific needs and orientations. Due to the limited pages of the main text and some of the contents have been partially covered by existing survey or research papers, we have moved the detailed explanations of the 1) latest advances, 2) classical methods, and 3) research cases to this supplemental material, in order to further enhance the readability of the main text and its value as an guidance for beginners. Specifically, Section 1 states the recent advances in UVAD, WsVAD, and FuVAD, summarizing their main contributions and implementations. Section 2 provides a summarized analysis of the classical methods, including the fundamental principles and architecture overview. Section 3 provides additional explanations of our research cases in smart cities and modern industries to promote the reader to conduct NSVAD research for real-world applications.

1 DETAILED PRESENTATION OF RECENT ADVANCES

1.1 UVAD Methods

1.1.1 GNL with Single Proxy Task. Table 1 summarizes the basic structures and main contributions of existing GNL models with single proxy tasks. Specifically, the Predictive Convolutional LSTM network (PC-LSTM) [56] stands out for its innovative use of a composite conv-LSTM network in predicting video sequence evolutions and using prediction errors to gauge normality scores, demonstrating the utility of LSTM in understanding temporal dynamics. Similarly, the Fully Convolutional Feedforward Autoencoder (FF-AE) proposed by Hasan *et al.* [26] highlights the shift towards end-to-end feature representation learning, using traditional handcrafted features to train anomaly classifiers. The Deep Incremental Slow Feature Analysis Network (D-IncSFA) [28] further advances this by learning from raw data, showcasing the en-to-end feature extraction capability. Smeureanu *et al.* [72] leverage a pre-trained VGG network for extracting deep spatial-temporal features, marking a pivotal move towards integrating deep learning with traditional AD techniques.

The introduction of video prediction tasks proposed proposed by Liu *et al.* [38], using GAN networks, marks a significant evolution, emphasizing the prediction of normalcy in events through generative models. This concept is expanded in FFPN [50], which explores predictive networks' design principles and meta-learning for scene adaptability, reinforcing video prediction's superiority in understanding video contexts. Li *et al.* [37] address the issue of detail loss in autoencoders with their Spatial-Temporal U-net (STU-net), blending U-net's spatial representation strength with ConvLSTM's temporal modeling prowess. AnomalyNet [100] and the Incremental Spatial-Temporal Learner (ISTL) [57] introduce novel approaches to background noise reduction and temporal anomaly evolution. Huang et al. [30] proposed a GAN-based UVAD framework, which includes a self-attentive predictor, a vanilla discriminator, and a self-supervised

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Table 1. Summary of Single Proxy Task-based GNL methods.

Ref.	Backbone	Contributions
2016 [28]	CNN	Building a deep incremental slow feature analysis network for learning abstraction and global high-level representation.
2016 [26]	AE	Designing a fully convolutional feed-forward AE to learn both local features and classifiers as an end-to-end framework.
2017 [15]	AE, GAN	Combining variational auto-encoder and GAN to model the spatial-temporal features of normal events efficiently.
2017 [48]	ConvLSTM, AE	Integrating CNN and ConvLSTM with auto-encoder to model the appearance and motion patterns of normal events.
2017 [72]	CNN	Using pre-trained CNN to extract appearance features and use OC-SVM to discriminate normal and abnormal events.
2018 [70]	CnovLSTM	Proposing a composite auto-encoder based on convolutional LSTM, 2D and 3D convolution to predict normal events.
2018 [38]	U-net	Detecting anomalies by measuring the difference between predicted and real frames with a prediction framework.
2019 [37]	ConvLSTM	Using U-net and convolutional LSTM based prediction framework to model spatial and temporal information efficiently.
2019 [100]	Sparse LSTM	Integrating feature learning, sparse representation, and dictionary learning in a unified framework to detect anomalies.
2019 [57]	ConvLSTM	Proposing incremental spatial-temporal learners to address the challenges of AD in real-time videos.
2019 [87]	U-net, ConvRNN	Unify reconstruction andprediction methods in an end-to-end deep predictive coding network framework.
2019 [24]	AE	Using memory to limit the generalization power of the AE and proposes a sparse addressing mechanism.
2019 [51]	ResNet, AE	Proposing a sparse coding-inspired neural network model for efficient video anomaly detection.
2020 [14]	3D ConvSLTM	Using 3D Conv-LSTM to model spatial-temporal features and use residual blocks to eliminate the gradient disappearance.
2020 [16]	U-net, GAN	Using two discriminators to improve the generator's ability to characterize the spatial-temporal patterns of normal events.
2020 [8]	U-net	Modeling the normality by performing forward and reverse frame prediction with two independent U-net.
2020 [62]	AE	Using an external memory network to weaken the generalization ability of the deep auto-encoder to anomalous events.
2021 [78]	ConvGRU	Using multi-path prediction framework to predict frames to better handle different scales of objects and regions.
2021 [50]	GAN, U-net	Identifying design principles for prediction-based VAD networks and designing a future frame prediction networks.
2022 [89]	GAN	Training predictive model to discriminate anomalies by the adversarial learning of past and future frames.
2022 [97]	PredRNN	Using ST-LSTM and adversarial learning to learn the evolution of motion and appearance in the short and long term.

discriminator. The self-attentive predictor captures long-term dependencies to improve the quality of normal frame prediction, while the two discriminators respectively perform real-fake discrimination and self-supervised rotation detection to enhance the representation of prototypical normal patterns.

Recent advancements include the Adversarial Event Prediction (AEP) network proposed by Yu *et al.* [89], using adversarial learning to discern abnormal events, and the ROADMAP model proposed by Wang *et al.* [78], which employs a multi-path convGRU for enhanced frame prediction. STC-Net [97] represents a leap forward with its focus on learning long- and short-term patterns, using adversarial learning to refine its capabilities. U-shaped Swin Transformer Network with Dual Skip Connections (USTN-DSC) [86] proposes keyframe-based video event recovery agent task to mine high-level visual features and temporal contextual relationships in videos. Cheng *et al.* [85] introduced a diffusion model to VAD in order to learn the distribution of normal samples without involving any additional advanced semantic feature extraction models. STR-VAD in [79] performs VAD by probing spatio-temporal relationships among objects.

An emerging concern is the potential for models to overgeneralize, making them less effective in distinguishing between normal and abnormal events. This is where memory networks, such as the Memory-enhanced Autoencoder (memAE) [24] and the attention-based memory network proposed by Park *et al.* [62], play a crucial role. These networks introduce mechanisms to limit model generalization, ensuring the memorization of normal event features and improving anomaly detection accuracy. The inclusion of memory networks has been a game-changer, offering a novel approach to balancing complex learning structures and the specificity required for effective anomaly detection. This evolution underscores the field's progression towards more nuanced and adaptable NSVAD models.

1.1.2 GNL with Multiple Proxy Tasks. Videos, as complex spatial-temporal series, offer a unique challenge in detecting anomalies, which may present as deviations in spatial appearance or temporal motion. Recognizing the need to address both dimensions, researchers have explored the use of multiple proxy tasks. These approaches not only model appearance and motion separately but also aim to understand the intricate relationships between these dimensions, such as consistency and correlation.

3D convolutional networks has inspired methods like the Spatial-Temporal Autoencoder (STAE) proposed by Zhao *et al.* [98], which models normality through dual decoders for reconstruction and prediction. A design mirrored in [58] also seeks to understand the correspondence between appearance and motion. Xu *et al.* [84] propose the Appearance and Motion DeepNet (AMDN), which utilizes separate autoencoders for learning from frames and optical flows, demonstrating the power of specialized descriptors in anomaly detection. The Prototype-Guided Dynamics Matching Network (PDM-Net) proposed in [29] introduces a long-short-term dynamic prototype alignment learning mechanism to model motion dynamics of different temporal lengths. It also proposes a feature discrimination module to handle the diversity of normal events.

The use of GANs in this domain, as explored by Ravanbakhsh *et al.* [65] and further developed in DD-GAN [16] and OGNet [91], highlights the adaptability of GANs to multiple proxy tasks. These models leverage GANs' ability to generate and discriminate, improving VAD by focusing on motion continuity and reconstruction fidelity.

Further contributions include Chang *et al.*'s [6] dual autoencoder approach for capturing distinct spatial and temporal information and the Dual-Stream Deep Spatial-Temporal Autoencoder (DSTAE) proposed by Li *et al.* [35], which emphasizes the role of convLSTM in temporal reasoning. The Appearance-Motion Joint Autoencoder framework proposed by Liu *et al.* [40] and STM-AE [43] showcase innovative strategies for fusing spatial and temporal features, with the latter introducing an external memory network to better capture normality patterns. The AnoPCN [87] model advances concept by integrating error refinement with deep predictive encoding.

Table 2. Summary of Spatial-Temporal Patch-based Methods.

Ref.	Patch Formulation	Detection Logic
2010 [54]	Slicing the video into equal-sized S&T patches	Deviation to learned dynamic textures
2013 [67]	Dense sampling at different spatial and temporal scales	Modeling S&T arrangements
2016 [101]	Equating video into $3 \times 3 \times 7$ pixel patches	Binary classification with FCN
2016 [12]	Slicing the video into equal-sized S&T patches	Learning normality prototypes
2017 [68]	Equating the video sequence and resizing the objects	Mahalanobis distance to Gaussian models
2017 [49]	Multiple patches sampled at multiple scales	Reconstruction error
2019 [77]	Foreground extraction and keeping only part regions	Reconstruction error
2020 [81]	Equating RGB video and corresponding optical flow frames	One-class classification
2021 [33]	Equating video sequences into spatial-temporal patches	Reconstruction error
2022 [39]	Equating frames into 8×8 pathches along spatial dimension	Prediction error for regions of interest

Recent works proposed by Cai *et al.* [4], Cheng *et al.* [11], and Ning *et al.* [59] underscore the growing interest in understanding the coherence between appearance and motion. These studies propose novel frameworks for leveraging the intrinsic consistency between these dimensions, aiming for a deeper comprehension of regular events. Hierarchical Semantic Contrast (HSC) in [74] introduces scene-level and object-level contrast learning to deal with the diversity of normal patterns to improve the model's ability to discriminate complex events.

1.1.3 LPM with Spatial-Temporal Patch (STP). STP methods are grounded in the assumption that anomalies manifest as deviations in local information. They address this by partitioning videos into information cubes, applying methods like Three-dimensional Equi-scale Segmentation (3D-ESE), Equi-spatial Information Intensity Segmentation (ESIIS), and High Information Density Filtering (HIDF) to model features independently. This approach enables nuanced understanding of spatial-temporal dynamics, catering to different densities of spatial information and filtering out irrelevant background for focused anomaly detection.

Innovations in this field include Deep-Cascade [68] and Spatial-Temporal Cascade Autoencoder (ST-CaAE) [33], both of which employ cascaded structures for local normality modeling, significantly reducing computational load by prioritizing regions of interest. S^2-VAE [77] highlights the use of foreground object detection in preprocessing to streamline input to variational autoencoders, optimizing the modeling of normality. DeepOC proposed by Wu *et al.* [81] and AST-AE proposed by Liu *et al.* [39] further refine this approach by integrating deep one-class classifiers and attention mechanisms to enhance anomaly detection efficiency.

1.1.4 LPM with Foreground Objects Detection (FOD). FOD methods, leveraging high-performance object detection models [66], offer an interpretable approach by analyzing specific attributes of foreground objects. This aligns closely with human intuition and has proven effective in complex scenarios like crowd anomaly detection. Techniques range from the LDGK model proposed by Ryota *et al.* [27], which utilizes multi-task learning for semantic information acquisition, to the DCF model [32], focusing on pose classification and motion modeling. The innovative use of visual cloze tests proposed by Yu *et al.* [88] and the Online Video Anomaly Detection (OAD) scheme proposed proposed by Doshi *et al.* underscore the significance of contextual information in enhancing anomaly detection.

Recent advancements include the Background-Agnostic framework [23], emphasizing instance segmentation to minimize background noise, and the OSIN network, which incorporates object detection to enrich scene understanding. Notably, Georgescu *et al.* [22] and the HF^2-VAD framework [46] introduce self-supervised learning tasks and hybrid modeling strategies, respectively, to achieve a comprehensive anomaly detection mechanism. The bidirectional prediction architecture (BiP) proposed by Chen *et al.* [7] and the Hierarchical Scene Normality-Binding Modeling (HSNBM) framework further exemplify the field's move towards integrating advanced prediction models and memory-augmented networks for a more detailed analysis of anomalies. Doshi *et al.* [17] propose a two-stream network to separately learn interactions between different targets and individual skeleton pose changes to perform interpretable VAD.

1.2 WsVAD Methods

Table 3. Summary of Unimodal WsVAD Models.

Ref	Fearure	Decision Logic	Contributions
2018 [73]	C3D	MIL ranking	Proposing to use video-level labels to supervise FCN to compute frame-level anomaly scores.
2019 [55]	ResNet-50, VGG-16	Binary classification	Using dual-stream CNNs to extract spatial and temporal features from video frames and optical flow.
2019 [99]	C3D, TSN^{RGB}, $\text{TSN}^{Optical\ flow}$	Action classification	Treating WAED as a supervised task under noise labels and using GCN to correct noise labels.
2019 [102]	VGG16, C3D, Inception, I3D	MIL ranking	Proposing a temporal-enhanced network to learn motion-aware features for MIL ranking model.
2020 [76]	I3D^{RGB}, $\text{I3D}^{Optical\ flow}$, I3D^{conc}	MIL ranking	Designing dynamic multi-instance learning loss and center loss for expanding the inter-class distance and reducing the intra-class distance of normal instances.
2020 [94]	C3D	MIL ranking	Using a clustering algorithm to generate pseudo-labels to assist the training of regression model.
2020 [92]	C3D	MIL ranking	Proposing a random batch-based training strategy to reduce the correlation between batches.
2021 [75]	C3D^{RGB}, I3D^{RGB}	MIL ranking	Proposing RTFM to explore the important temporal correlations for identification of positive instances.
2021 [53]	I3D	MIL ranking	Fusing S&T contexts to perform weakly-supervised video anomaly localization while proposing an enhancement strategy to eliminate noise interference.
2021 [20]	C3D^{RGB}, I3D^{RGB}	MIL ranking	Using a generator to generate reliable pseudo labels and extract task-specific deep representations.
2022 [31]	C3D	MIL ranking	Proposing a deep temporal coding scheme to capture the temporal evolution of video examples over time, reducing the false alarm rate of anomaly detection.
2022 [96]	I3D^{RGB}	MIL ranking	Exploring the temporal relationships between video clips, and capturing the task-specific features.
2022 [34]	CNN	Binary classification	Using 2D convolutional networks and echo state networks to obtain local ratio representations, and then using 3D convolutional networks to extract spatial-temporal features.
2022 [41]	I3D	MIL ranking	Using RNNs to capture temporal correlations and using a clustering algorithm to generate pseudo-labels for the training of MIL regression model.
2022 [44]	C3D^{RGB}, I3D^{RGB}	MIL ranking	Proposing recurrent criss-cross attention to explore the connection between local S&T representations.

1.2.1 Unimodal Methods. We have summerized the decision logic and main contributions of existing unimodal WsVAD models in Table 3. Specifically, Snehashis *et al.* [55] utilized a dual-stream CNN for spatial and temporal feature extraction, comparing architectures like ResNet 50 and Inception V3. Zhu and Newsam [102] emphasized motion information's importance, proposing a Temporal Augmented Network for motion-aware feature learning. Zhong *et* *al.* [99] approached WAED as a supervised task with noisy labels, suggesting graph convolutional networks for label rectification. The Anomaly Regression Net (ARNet) [76] and a two-stage framework proposed by Waseem *et al.* [34] focused on discriminative feature learning and spatial-temporal feature fusion, respectively.

Tian *et al.* [75] introduced Robust Temporal Feature Metric Learning (RTFM) employing dilated convolutions and self-attention for accurate feature learning. Muhammad *et al.* [94] used clustering for pseudo-label generation, introducing a clustering loss for enhanced anomaly detection. The CLAWS model [92] proposed a random batch training strategy and a clustering distance-based loss to handle label noise.

Ammar *et al.* [31] developed a Deep Temporal Encoding-Decoding (DTED) solution for capturing spatial-temporal evolution patterns, employing joint loss optimization. The Weakly Supervised Temporal Relation Learning (WSTR) [96] utilized transformer technology for mining semantic correlations, while the Within-Video Abnormality Spotting and Localization (WASL) [53] focused on fusing temporal and spatial contexts with high-order context encoding.

Lastly, Feng *et al.* [20] presented a Multi-Instance Self-Training (MIST) framework for generating reliable pseudo-labels and extracting task-specific representations. Liu *et al.* [41] introduced a Self-guiding Multi-instance Ranking (SMR) framework using clustering for pseudo-label generation and exploring task-relevant features. The Spatial-Temporal Attention (STA) framework [44] aimed at understanding the relationship between local and global features, employing recurrent cross-attention operations for feature enhancement. In response to the vulnerability of MIL to anomalous fragments with simple contexts that lead to high false alarms, Lv *et al.* [52] proposed Unbiased MIL (UMIL) to eliminate contextual bias. Chen *et al.* [10] propose a feature amplification mechanism and amplitude contrast loss to enhance the discrimination of feature amplitude detection anomalies

1.2.2 Multi-modal Methods. Wu *et al.* [82, 83] introduced HL-Net, a three-branch network for violence behavior detection that employs similarity and proximity priors for capturing long-distance correlations and local positional relations, alongside a score branch for dynamic proximity capture. Pang *et al.* [61] proposed a feature fusion network that utilizes a bilinear pooling mechanism for visual and audio information fusion, facilitating mutual learning for enhanced feature representations in multi-modal violence detection tasks. The Modality-aware Contrastive Instance Learning with Self-Distillation strategy [90] addresses modality heterogeneity through lightweight dual-stream networks and a self-distillation module that bridges the semantic gap between multi-modal features.

Wei *et al.* [80] proposed the Multi-modal Supervised Attention Fusion (MSAF) framework for implicit multi-modal data alignment, refining video-level ground truth into pseudo-clip-level labels and employing attention fusion guided by these labels for feature fusion and anomaly score prediction. Shang *et al.* [69] tackled the challenge of dataset limitations by proposing mutual distillation to transfer knowledge from larger to smaller datasets, along with a multi-modal attention fusion strategy for more discriminative feature representations. The Audio-Guided Attention Network (AGAN) [63] extracts video and audio features, enhances them temporally through the cross-modal aware local awakening network, and computes anomaly scores with temporal convolution, showcasing the potential of multi-modal approaches in overcoming the constraints of current VAD research.

Text Empowered Video Anomaly Detection (TEVAD) [9] computes text features using subtitles of videos to capture the semantics of anomalous events. Zhang *et al.* [95] propose an enhanced two-stage self-training framework that utilizes completeness and uncertainty properties. Feng *et al.* [19] use a feature set that captures the temporal synchronization between video frames and sound to train an autoregressive model to generate audiovisual feature sequences for video forensics. Multimodal Motion Conditioned Diffusion [21] considers skeletal representation and utilizes SOTA diffusion model to generate multimodal future human poses.

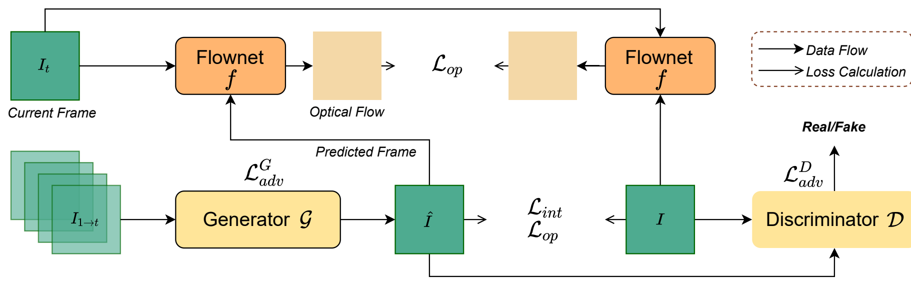

Fig. 1. Overview of the Future Frame Prediction framework. FFP consists of a pre-trained optical flow network [18] f, a generator $\mathcal{G}$, and a discriminator $\mathcal{D}$. During training, $\mathcal{G}$ accepts a continuous sequence $\boldsymbol{I}_{1:t}$ of t frames as input to predict the next frame $\hat{\boldsymbol{I}_{t+1}}$, while $\mathcal{D}$ attempts to differentiate between the predicted frame $\hat{\boldsymbol{I}_{t+1}}$ and the real future frame $\boldsymbol{I}_{t+1}$. The learnable parameters of $\mathcal{G}$ and $\mathcal{D}$ are optimized with optical flow loss $\mathcal{L}_{op}$, intensity loss $\mathcal{L}_{int}$, gradient losses $\mathcal{L}_{gd}$, and adversary loss $\{\mathcal{L}_{adv}^{D}, \mathcal{L}_{adv}^{G}\}$.

2 DETAILED EXPLANATION OF CLASSICAL METHODS

2.1 UVAD

2.1.1 Future Frame Prediction (FFP) Framework. FFP [38] introduces the prediction proxy task into UVAD for the first time, laying the research foundation for prediction methods. The authors believe that traditional reconstruction proxy tasks based on autoencoders, while easy to train, may be ineffective in detecting anomalies due to the strong learning ability of deep neural networks on simple tasks, leading to missed detections. In contrast, Video Prediction (VP) requires models to explicitly demonstrate the spatial-temporal pattern evolution of inferred video data, empowering models to understand the internal logic of regular events. Therefore, they propose the video prediction framework shown in Fig. 1, which is based on the assumption that predictors (i.e., generators $\mathcal{G}$) learned on massive regular events cannot infer the appearance and motion information of unseen anomalous samples. Inspired by the successful application of GANs in VP tasks, the core components of the FFP framework are a U-Net-based generator $\mathcal{G}$ for predicting future frames and a patch discriminator $\mathcal{D}$ introduced from the Least Square GAN.

During the training phase, the $\mathcal{G}$ based on U-net accepts t consecutive frames $\boldsymbol{I}_{1:t}$ as input and attempts to predict the next frame, while the $\mathcal{D}$ attempts to differentiate between input images as real or predicted. The authors introduce intensity, gradient, and optical flow constraints to measure the differences between predicted $\hat{\boldsymbol{I}}$ and ground truth future frames $\boldsymbol{I}$ from spatial appearance, temporal motion, and gradient perspectives, denoted as $\mathcal{L}_{int}$, $\mathcal{L}_{gd}$, and $\mathcal{L}_{op}$, respectively. Additionally, the generator and the discriminator enhance each other through adversarial learning. The objective function of $\mathcal{D}$ is to discriminate $\boldsymbol{I}$ as real and output 1 for $\hat{\boldsymbol{I}}$. While $\mathcal{G}$ aims to generate as realistic predicted frames as possible that can be recognized as 1 by $\mathcal{D}$.

During the testing phase, FFP only uses the well-trained $\mathcal{G}$ to predict the next frame and quantitatively calculates the degree of anomaly by measuring the difference between the output and ground truth. Specifically, the authors use Peak Signal-to-Noise Ratio (PSNR) to calculate the quantitative difference between $\boldsymbol{I}$ and $\hat{\boldsymbol{I}}$. To better illustrate the relationship between this value and the degree of anomaly, PSNR of all frames of the same test video is normalized to the anomaly score s in the range [0,1] using max-min normalization. Since the larger the difference between images, the smaller their PSNR, a smaller s indicates a higher degree of anomaly.

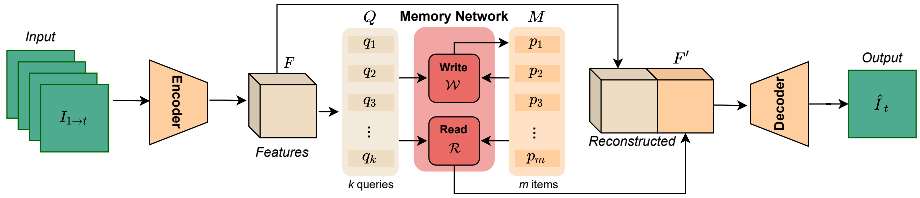

Fig. 2. Pipeline for Memory-Guided Video Normality Learning (MGVNL). MGVNL utilizes a memory network $\mathcal{M}$ to store prototype patterns of normal events to limit the overgeneralization of encoder and decoder to anomalies.

FFP utilizes the unique temporal structure information of video as self-supervised signals to learn video normality, opening up a new track of video self-supervised learning for UVAD—future frame prediction. Subsequent research has shown that even with the similar network, prediction proxy tasks can achieve additional performance gains compared to reconstruction, completely distinguishing VAD research from conventional AD tasks on non-temporal data. Most of the prediction-based UVAD models also use GAN as backbone and introduce optical flow to learning temporal dynamics with inspiration from FFP. Moreover, FFP framework is easy to implement and shows significant performance improvements through new proxy tasks, inspiring following researchers to focus on efficient proxy task design. They have proposed a series of video-specific tasks for normality learning, such as bidirectional prediction, spatial-temporal puzzles, and stochastic motion representation, whihc significantly advance the development of UVAD.

2.1.2 Memory-Guided Normality Learning. AD community always emphasizes the diversity of anomalies, thus unsupervised methods only use easily identifiable regular events to train models, thereby avoiding defining and collecting rare diverse anomalies. However, a long-standing problem is that the spatial-temporal features of regular events are also diverse and exhibit a wide range of pattern overlap with anomalous events, which may result in models trained on normal samples effectively reconstructing anomaly samples through learned diverse normal patterns, even without having seen them. Numerous studies have shown that deep neural networks may characterize abnormal events with small reconstruction/prediction errors due to excessive generalization. To address this, Park *et al.* [62] proposed Memory-Guided Video Normality Learning, which embeds an external memory network $\mathcal{M}$ between the encoder and decoder to weaken the generalization ability of deep models, as shown in Fig. 2. Experiments show that the memory network brings considerable performance improvement to UVAD with low training cost and parameter count, eliminating obstacles for large-scale video representation models in the VAD application. Many subsequent UVAD studies have referenced this work using memory networks to constrain the overgeneralization of deep neural networks and proposed new addressing mechanisms and optimization strategies.

The memory network is essentially a 2D matrix, denoted by $\boldsymbol{M} = \{\boldsymbol{p}_1, \boldsymbol{p}_1, \cdot, \boldsymbol{q}_m\} \in \mathbb{R}^{m\times C}$, which contains m items of dimension C and is embedded between the encoder and decoder. During training, $\mathcal{M}$ writes the prototype patterns of spatial-temporal features $\boldsymbol{F} \in \mathbb{R}^{H\times W\times C}$ extracted by the encoder into $\boldsymbol{M}$ through write operation, and then uses historical memory items through read operations to construct $\boldsymbol{F'}$. The decoder uses the concatenated $\boldsymbol{F'}$ and $\boldsymbol{F}$ as input to reconstruct input sequences or predict future frames. During testing, the concatenated features of regular events are similar to $\boldsymbol{F}$ and can be effectively understanded by the decoder, while the that of unseen abnormal events will deviate significantly, leading to large decoding errors. First, $\boldsymbol{F}$ is unfolded along the spatial dimension into k query vectors, denoted as $\boldsymbol{Q} = \{\boldsymbol{q}_1, \boldsymbol{q}_1, \cdot, \boldsymbol{q}_k\} \in \mathbb{R}^{k\times C}$, where $k = H \times W$. The read operation aims to reconstruct $\boldsymbol{q}_i$ using memory items from $\boldsymbol{M}$: $\boldsymbol{F} \longleftarrow \hat{\boldsymbol{q}} = \boldsymbol{w}_i\boldsymbol{M}$, where $\boldsymbol{w}_i \in \mathbb{R}^{1\times m}$ denotes the weighting coefficient. In [62], $\boldsymbol{w}$ is defined as the cosine similarity between $\boldsymbol{q}_i$ and al items, followed by softmax normalization. The write operation uses $\boldsymbol{Q}$ to update $\boldsymbol{M}$

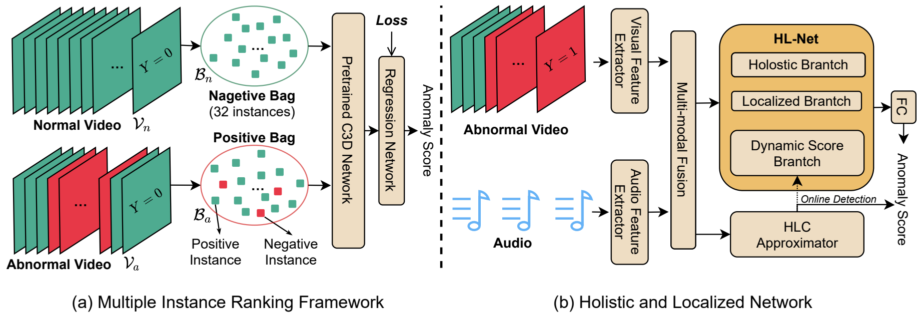

Fig. 3. Architecture overview of **(a)** Multi-Instance Ranking (MIR) framework and **(b)** Holistic and Localized Network. The MIR employs a regression network to calculate anomaly scores with the supervision from video-level labels. The HN-Net aims to mine anomaly cues from both video and audio to enhance the performance of the MIL framework in violence detection.

to record prototype patterns of regular events. Similar to the read operation, the weighting coefficient is defined as the normalized cosine similarity between $\boldsymbol{p}_i$ and all query vectors. To ensure the numerical scale of memory items remains comparable during the update process, the authors perform $\mathbf{L}_2$ normalization on the weighted memory items: $\boldsymbol{M} \leftarrow \hat{\boldsymbol{p}}_i = \mathbf{L}_2(\boldsymbol{p}_i + \boldsymbol{w}_i \boldsymbol{Q})$.

In recent years, researchers have improved the addressing mechanisms and optimization strategies of memory networks. For example, Lv *et al.* proposed using attention networks to calculate weight coefficients during the update process and first embedded the memory network into the decoder to further enhance the model's learning ability for event prototypes. MSN-net uses loss functions inspired by information theory to constrain memory entry updates and proposes a Top-k attention-based addressing mechanism to alleviate the negative impact of event diversity on prototype feature learning.

2.2 WsVAD

2.2.1 *Multiple Instance Ranking (MIR) framework.*

MIR [73] introduced video-level labels into VAD task and proposed the MIL-based weakly supervised route. Its basic structure is illustrated in Fig. 3(a), comprising a pre-trained C3D network for spatial-temporal feature extraction and a regression network for calculating frame-level anomaly scores. In contrast to UVAD models in Fig. 1 and 2, WsVAD have access to pre-defined anomaly samples and video-level labels Y during training. MIR first divides the video into 32 non-overlapping fixed-length segments, each containing 16 consecutive frames. The authors treat each segment as an instance, and all instances from the same video constitute a bag. Clearly, all instances in the negative bag $\mathcal{B}_n$ formed by normal videos $\mathcal{V}_n$ are negative, while only a few instances in the positive bag $\mathcal{B}_a$ are positive.

MIR frames the VAD under the supervision of video-level labels as a regression problem, aiming to use weak-semantic annotations to supervise a fully connected network (FCN) to output instance-level anomaly scores ranging from [0, 1], where higher scores indicate a higher likelihood of anomalies. An intuitive optimization strategy is to use the ranking loss, denoted as $f(\mathcal{V}_a) > f(\mathcal{V}_n)$, which encourages the regression network to output higher scores for $\mathcal{V}_a$. However, during the training phase, only video-level labels are available, meaning that it is known whether the input video contains anomalies, but the specific temporal positions of anomalies are unknown. Inspired by MIL, the authors propose a multi-instance ranking loss to encourage the highest score of instances in $\mathcal{B}_a$ to exceed that in $\mathcal{B}_n$:

$\max_{i\in\mathcal{B}_a} f\left(\mathcal{V}_a^i\right) > \max_{i\in\mathcal{B}_n} f\left(\mathcal{V}_n^i\right)$. Furthermore, drawing from the Hinge loss in SVM for classification, this objective equation is optimized as $\max\left(0, 1-\max_{i\in\mathcal{B}_a} f\left(\mathcal{V}_a^i\right)+\max_{i\in\mathcal{B}_n} f\left(\mathcal{V}_n^i\right)\right)$. Additionally, considering the sparsity of positive instances in $\mathcal{B}_a$ and the continuity of events, MIR introduce sparsity constraint $C_{sparsity}$ and smoothness constraint $C_{smoothness}$. Regularization constraints are added to the model weights $\boldsymbol{W}$ to prevent overfitting. Therefore, the final objective function was balanced with hyper-parameters $\{\lambda_1, \lambda_2\}$, as follows:

$$l\left(\mathcal{B}_a, \mathcal{B}_n\right) = \max\left(0, 1-\max_{i\in\mathcal{B}_a} f\left(\mathcal{V}_a^i\right)+\max_{i\in\mathcal{B}_n} f\left(\mathcal{V}_n^i\right)\right) + \lambda_1 \overbrace{\sum_i^{n-1)} \left(f\left(\mathcal{V}_a^i\right) - f\left(\mathcal{V}_a^{i+1}\right)\right)^2}^{C_{smoothness}} + \lambda_2 \overbrace{\sum_i^{n} f\left(\mathcal{V}_a^i\right)}^{C_{sparsity}}, \tag{1}$$

Researchers follow the MIL ranking of MIR and have proposed many innovative WsVAD works, driving model performance improvement and field development. Mainstream UVAD solutions, such as reconstruction/prediction-based models, require obtaining the entire video first and then performing offline detection. In contrast, WsVAD methods like MIR can online output anomaly scores for continuous video streams, promoting the application of VAD in IoVT.

2.2.2 Holistic and Localized Network. To fully unleash the potential of deep learning in multimodal violence detection, Wu *et al.* [82] collected a large-scale violence behavior dataset with weak semantic annotations, comprising video and audio files, pioneering research in multimodal VAD. This section focuses on the Holistic and Localized Network (HLN) proposed by them as a case study for video-audio anomaly detection under weak supervision settings. The core structure of the HLN network is illustrated in Fig. 3(b), consisting of three parts: data preprocessing, offline detection, and online detection units. The authors first extract deep features for video and audio separately using the I3D and VGG networks, which are then concatenated along the channel dimension and fed into a fully connected network for fusion. The HL-Net comprises holistic and localized branches, designed to capture long-range and short-range relationships in the fused video-audio features, respectively. Inspired by graph neural networks, the holistic branch employs feature similarity to define the overall relationship matrix. Additionally, the localized branch considers position distances in non-local operations using a proximity-based local relationship matrix. Since the aforementioned HL-Net requires access to the entire video due to its long-range dependencies, it cannot perform online detection, which is crucial for intelligent surveillance systems. To address this, the authors introduce a Holistic and Localized Cue (HLC) approximator, used under the guidance of HL-Net to generate accurate predictions using past video segments. Furthermore, the dynamic score branch computes the response at a particular position as the weighted sum of features from all positions, further enhancing online detection performance. Due to the availability of only video-level labels, the training of the above modules still follows multiple instance learning.

2.3 FuVAD

2.3.1 Self-trained Deep Ordinal Regression. The basic structure of SDOR is shown in Fig. 4(a), consisting of an initial anomaly detection module, feature extractor, and anomaly scorer. Unlike unsupervised methods that rely on carefully curated training data, SDOR utilizes imbalanced normal and anomaly samples without any labels available. The authors argue that such a setup can avoid the costs of data curation and labeling, enabling the model to directly learn from massive amounts of raw real-world videos, extending NSVAD applications to online video content detection. Furthermore, in SDOR, feature learning and score training are jointly optimized, avoiding the suboptimal model performance due to excessive reliance on pre-trained feature extractor in WsVAD. Specifically, the authors first use Isolation Forests on non-specifically oriented video data to separate potentially anomalous instances with significant

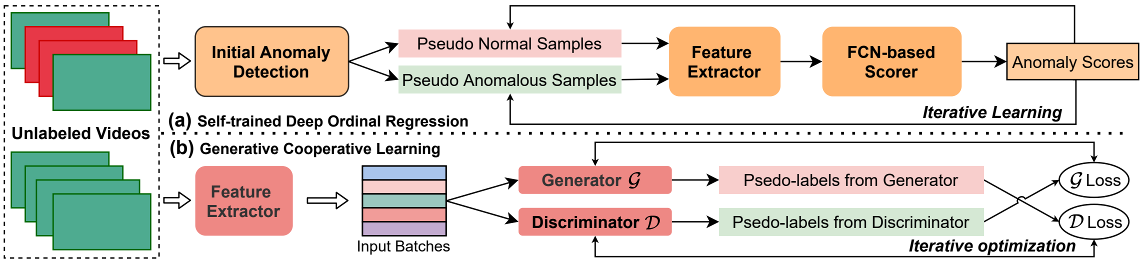

Fig. 4. Architecture overview of (a) SDOR [60] and (b) GCL [93].

differences from the raw data, then employ such pseudo-samples to supervise both the feature extraction module and anomaly scorer. Given that label noise from initial pseudo-samples may lead to inaccuracies in the output anomaly scores, SDOR introduces iterative learning to update pseudo-labels.

2.3.2 Generative Cooperative Learning. In contrast to the adversarial learning in GANs [71], GCL employs a cooperative learning between generator $\mathcal{G}$ and discriminator $\mathcal{D}$ to optimize each other, as shown in Fig. 4(b). Specifically, $\mathcal{G}$ is implemented as an autoencoder tasked with reconstructing the features of input videos. Based on reconstruction errors and a threshold, $\mathcal{G}$ labels the input as pseudo-normal or pseudo-anomalous, where the pseudo-labels are used to train $\mathcal{D}$. For pseudo-anomalies with high confidence (samples with significantly large feature reconstruction errors), the authors introduce negative learning to encourage $\mathcal{G}$ to further exaggerate the errors. The $\mathcal{D}$ is a simple fully connected network, used to compute the anomaly probability of input samples for supervising $\mathcal{G}$.

In implementation, the authors employ ResNext3d [25] as the feature extractor to characterize unlabelled video sequences. To eliminate the covariate shift between intra-batch and inter-batch features, they perform random sampling on feature vectors to constitute input batch features for $\mathcal{G}$ and $\mathcal{D}$. $\mathcal{G}$ is trained in a self-supervised learning manner, where the loss is defined as the MSE between input and reconstructed features. According on the low frequency of anomalies, the authors regard samples whose reconstruction errors rank within the top fixed percentage as pseudo-anomalies. In contrast, $\mathcal{D}$ is trained using pseudo-labels generated by $\mathcal{G}$, aiming to minimize the binary cross-entropy loss. The process of generating pseudo-labels for $\mathcal{D}$ mirrors that of $\mathcal{G}$, where samples with high probability values exceeding a predefined threshold are considered anomalies. For the pseudo abnormal samples identified by $\mathcal{G}$, the authors adjust the output targets during $\mathcal{G}$'s training process to be a vector of all ones rather than the input features, thereby further exaggerating the reconstruction errors between anomalies and normals.

3 RESEARCH CASES

In this section, we present research cases that demonstrate the practical application of NSVAD technologies in emerging scenarios such as smart industries and smart cities. These cases illustrate both the potential and challenges of deploying NSVAD in real-world environments.

3.1 Appearance-Motion Prototype Network for Smart Industry

Due to the presence of multiple entities (e.g., humans, machines, and products) with complex spatial-temporal interactions in modern factories, NSVAD for smart industries faces significant system-level challenges compared to simpler scenarios like public spaces where anomalies are primarily human-centric. Inspired by the UVAD anomaly categorization principles and memory networks, we identified that the key to effective NSVAD in dynamic industrial environments lies in efficiently representing diverse normal patterns while maintaining limited generalization to possible anomaly events.

Through observations of manufacturing processes, we categorized industrial anomalies into three types: appearance-only (e.g., humans entering machine workspaces and foreign objects intruding on assembly lines), motion-only (e.g., sudden acceleration or abrupt stops of robotic arms), and appearance-motion united anomalies (e.g., product drops due to failed grabs). This systematic categorization informed our design of AMP-Net [42], a spatial-temporal memory augmented three-branch network that explores prototype patterns of regular events across multiple dimensions and scales, as shown in Fig. 5.

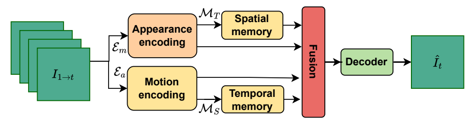

Fig. 5. Structure overview of the AMP-Net.

Unlike existing multi-stream approaches [43] that do not distinguish between static appearance and dynamic motion, AMP-Net employs specialized encoding networks for appearance ($\mathcal{E}_a$) and motion ($\mathcal{E}_m$), with $\mathcal{E}_a$ focusing on local spatial contexts and $\mathcal{E}_m$ on global temporal changes. We introduced a fusion module based on channel attention to enhance multi-level appearance semantics and temporal attention to actively capture important dynamics. Additionally, we implemented memory networks in both branches to store prototype features of regular industrial videos while preventing overgeneralization to anomalies.

Experimental results on real industrial datasets demonstrated AMP-Net's significantly higher detection capabilities for complex industrial anomalies compared to contemporaneous UVAD schemes. The system achieved frame-level AUCs of 98.7%, 92.4%, and 78.8% on UCSD Ped2 [36], CUHK Avenue [47], and ShanghaiTech [38] datasets respectively. More importantly, these results validate that NSVAD can effectively extend from simpler campus scenarios to complex industrial environments, detecting various manufacturing anomalies and enhancing industrial process safety.

3.2 Causal Video Normality Learning for Smart Cities

Smart cities present unique system-level challenges for NSVAD deployment. Regular videos from real-world urban environments often contain label-independent data shifts due to equipment specifications, acquisition angles, and external weather conditions. Moreover, some potentially severe anomalies (such as vehicles traveling against traffic flow) exhibit subtle differences from regular events in spatial-temporal patterns. Existing deep learning models often struggle to generalize effectively to regular events with data shifts while remaining sensitive to minor anomalies. To address these smart city-specific challenges, we proposed Causal Video Normality Learning (CVNL) [45], which uncovers potential causal relationships in video regularity to handle diverse events in complex urban environments.

As illustrated in Fig. 6, CVNL consists of: *a*) feature extractor, *b*) memory, *c*) prototype decomposer, and *d*) causally inspired characterizer. The prototype decomposer separates shared semantics from personalized semantics in video features, while the causally inspired characterizer explores potential causal variables that determine video regularity. Inspired by causal representation learning

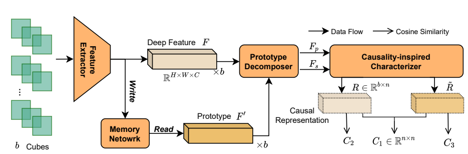

Fig. 6. Pipeline of causal video normality learning.

principles, CVNL identifies anomalies based on causal consistency in regular events rather than simple statistical dependencies.

The method achieved significant performance gains in cross-scenario testing, maintaining robust performance even when faced with scene transitions (such as from vehicle lanes to storefronts in the ShanghaiTech dataset). This robustness to data shifts demonstrates CVNL's potential for deployment in smart city environments where surveillance cameras capture diverse urban scenes under varying conditions.

4 BENCHMARK DATASETS

4.1 Unsupervised Datasets

Subway [2] focuses on abnormal event detection in subway stations, comprising two subsets: Entrance and Exit, with abnormal behaviors. The entrance is used to detect fare evasion behaviors like jumping over turnstiles. In contrast, abnormal events in the Exit include 1) appearance anomalies, such as cleaners wearing attire different from regular passengers, and 2) motion anomalies, such as people walking in the opposite direction of the exit. This dataset was collected 20 years ago, so its resolution is low. Moreover, due to overly coarse annotations and lack of clear rules defining abnormal events, recent VAD works have discontinued using this dataset. Therefore, we recommend researchers to use larger and more clearly annotated datasets, such as UCSD Ped2, CUHK Avenue, and ShanghaiTech, for validation.

UMN [13] consists of 11 long video sequences captured from 3 different scenes. Unlike Subway, this dataset includes behaviors pre-set by the collectors and volunteers acting them out. Abnormal events are defined as sudden evacuations caused by panic in crowds, simulating mass anomalies in the real world due to terror attacks and fires. Due to the lack of convincing application scenarios, neglect of diversity, and low frequency of real-world anomalies, this dataset is no longer used in UVAD.

UCSD Pedestrian [36] is one of the most widely used UVAD benchmarks collected by researchers from the campus of University of California, San Diego. Due to its realistic scenes and clear definition of abnormal events, it is widely used to evaluate models' potential applications in public safety. According to camera angles, UCSD Pedestrian is divided into Ped1 and Ped2 subsets. The latter is more favored by existing methods because the camera view is parallel to the road direction, eliminating the problem of changing object sizes with spatial changes. Recent methods have achieved remarkable frame-level AUCs exceeding 98% on UCSD Ped2, while the best performance on Ped1 is still below 94%, indicating that performance on Ped2 has saturated. Considering that cross-view videos are inevitable in the real world, we recommend that future researchers consider using Ped1 for validating and empowering UVAD models to overcome perspective issues. Some researchers move abnormal samples from the test set of UCSD Ped2 to the training set to meet the requirements of weakly supervised training, proposing a reconstructed UCSD Ped2 dataset for WsVAD testing.

CUHK Avenue [47] is similar to UCSD Pedestrian in scene selection and data structures, with only the test set containing 47 abnormal events captured from a university campus. However, CUHK Avenue considers more realistic situations. Collectors collected appearance-only, motion-only, and appearance-motion united anomalies to comprehensively simulate the diversity and complexity of real-world anomalies. Therefore, the appearance and motion patterns of videos in CUHK Avenue are more complex, making it one of the most challenging UVAD benchmarks. Additionally, CUHK Avenue inspired later researchers to collect UVAD datasets by simulating abnormal behaviors, such as ShanghaiTech [38] and NWPU Campus [5].

ShanghaiTech [38] breaks the single-scene limitations of UCSD Ped2 and CUHK Avenue, collecting 158 abnormal events from 13 scenes. Compared to the above datasets, it has a larger data scale and more complex anomaly types.

Therefore, the performance of existing UVAD methods on ShanghaiTech is generally lower (AUC < 80%), indicating the need for further exploration in cross-scene UVAD [3]. Moreover, researchers proposed ShanghaiTech Weakly for WsVAD. Recent studies have shown that with similar scenarios and anomalies, the performance of WsVAD methods on the re-organized dataset significantly outperforms UVAD models on the original one. For example, mainstream WsVAD models like MIST [20] and RTFM [75] achieve a frame-level AUC of up to 98%, surpassing state-of-the-art UVAD by nearly 20%. This phenomenon indicates that weakly supervised methods are more applicable in real-world scenarios.

Street Scene [64] dataset is the first UVAD benchmark dedicated to anomaly detection in complex traffic, suitable for validating models' deployment potential in smart city applications. The authors used static USB cameras to collect real street scenes (sidewalks, bike lanes, and roadways) in Cambridge, Massachusetts, USA, covering various traffic participants like pedestrians, non-motorized vehicles, and motor vehicles. Following the UVAD task setting, all 46 training videos depict normal events, while 35 test samples contain 205 abnormalities categorized into 17 classes. This dataset contains rich traffic behaviors, such as vehicle-centric driving, turning, and stopping, pedestrian-centric walking, jogging, and pushing strollers, and non-motorized vehicle-centric biking. Additionally, due to daylight angle changes, handling this dataset also requires addressing the effects of building shadows and moving backgrounds in urban scenes. Apart from temporal annotations, collectors also provided trajectory-level annotations, i.e., bounding boxes and IDs marking the boundaries of anomalies for fine-grained spatial localization learning.

NWPU Campus [5] is currently the largest UVAD dataset, containing 547 videos collected from 43 scenes, totaling 76.6*GB*. Its data scale, scene quantity, and abnormal class diversity exceed those of existing unsupervised datasets, allowing for thorough testing of model effectiveness and generalization. It's worth noting that the collectors considered the scene relevance of abnormal events, meaning similar behavioral patterns might be classified as different categories in different scenes. Therefore, during data collection, they simulated such behaviors extensively to enhance the dataset's consistency with real-world scenes.

4.2 Weakly Supervised Datasets

UCF-Crime [73] established the first benchmark for WsVAD and continuously promoted weakly supervised methods based on MIL. This dataset collected 1,900 unedited surveillance videos from the internet containing 850 crime events such as theft, robbery, and road accidents. Collectors categorized these anomalies into 13 classes, labeling videos containing such events as 1, while others were labeled as 0. This weak semantic annotation, termed video-level labels, is used to supervise model learning of finely detailed frame-level labels with solid semantics. Unlike UVAD, which only uses regular videos for model training, the UCF-Crime training set contains positive and negative samples, learning the differences between normal and abnormal by contrasting their pattern differences. The anomalies defined in WsVAD align more with human recognition and have a higher degree of realism. Since predefined abnormal events are seen during the training phase, WsVAD exhibits more stable performance in detecting specific category anomalies, with less susceptibility to scene changes and external environmental influences. Subsequent weakly supervised datasets, such as XD-Violence [82] and these reconstructed from UVAD datasets like UCSD Ped2 and ShanghaiTech, also follow the data settings of UCF-Crime, with both training and testing sets containing positive and negative samples. However, the UCF-Crime dataset assumes VAD is a closed-set problem, as abnormal events in the test set have all appeared in the training set, thus unable to verify the model's ability to discriminate anomalies in an open world.

XD-Violence [82] is the first mainstream large-scale VAD benchmark with multimodal data, including videos and synchronized audio. The authors collected various violent behaviors endangering personal safety from the internet as target anomalies, including riots, aggressions, shootings, and traffic accidents. Besides real surveillance videos from the internet, this dataset also includes audiovisual files from games and movies, significantly increasing the detection difficulty. XD-Violence opens a new avenue for VAD research, i.e., mining anomaly-related clues from heterogeneous data. Consistent with UCF-Crime [73], XD-Violence provides coarse semantic video-level annotations. Each video only requires one label without annotating specific categories of anomalies, making the data preparation cost acceptable. Since the collectors did not consider the open-set characteristics of AD tasks, the anomaly event categories in the training and testing sets are consistent. Therefore, this dataset can only be used to test closed-set models. We recommend that future researchers place unseen anomalies in the testing set to develop multimodal VAD models with open-set detection capabilities.

TAD [53] is a weakly supervised VAD dataset for anomaly detection in traffic scenes. The authors collected 25 hours of traffic surveillance videos from urban and rural environments, including 250 normal and 250 abnormal instances, with 400 videos used for training and 100 for testing. The anomalies include vehicle accidents, illegal turns, illegal occupations, retrograde motion, pedestrians on the road, road spills, and other low-frequency events.

4.3 Supervised Datasets

The high cost of collecting anomalies and fine-grained annotations makes existing VAD research typically avoid supervised learning requiring frame-level or pixel-level supervision. However, the rise of virtual data engines has made it feasible to construct diverse abnormal events and synchronously obtain precise labels. To this end, Acsintoae *et al.* [1] constructed the first supervised VAD dataset named **UBnormal** by simulating virtual anomalies, providing a reference for addressing the data and label preparation challenges with virtual engines. In addition, this dataset can address the close-set concern of WsVAD tasks. The authors set up a validation set, including positive samples of different categories from the training set, to encourage models to detect unseen anomalies.

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