MemoVAD: Resource-Efficient Video Anomaly Detection via Dynamic Semantic Memory in Edge Computing Scenarios

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Abstract

Deploying Video Anomaly Detection (VAD) in real-world surveillance faces a fundamental tension between the demand for high-level semantics to ensure effectiveness and the limited computational resources of edge devices. Vision–Language Models (VLMs) provide rich open-vocabulary semantics, but their latency and computational cost preclude on-device deployment. To address the challenge, we propose MemoVAD, an edge–cloud collaborative framework that selectively incorporates VLM semantics into streaming VAD. MemoVAD runs most inference on the edge with a lightweight detector and a causal Temporal Context Encoder (TCE) to model temporal dependencies. Specifically, we introduce an Uncertainty-Aware Gating (UAG) policy grounded in Subjective Logic to model perceived uncertainty and query the cloud-based VLM only for high-uncertainty and semantically novel clips. Besides, a Dynamic Semantic Memory (DSM) is designed to cache VLM-verified prototypes for efficient retrieval, enabling the edge model to progressively absorb VLM-level semantics via a semantic adapter. Experiments on UCF-Crime and XD-Violence datasets via a real edge device show that MemoVAD substantially reduces communication overhead while surpassing state-of-the-art performance. The demo video is available at: https://memovad2026.github.io/.

1 Introduction

The widespread deployment of surveillance cameras in public spaces has resulted in an explosive growth of video data, creating an urgent demand for automated Video Anomaly Detection (VAD) [Shathik, 2025]. The primary objective of VAD is to identify abnormal events, such as accidents or criminal activities, within long sequences of normal activities. While recent advancements in deep learning have significantly improved detection accuracy, deploying the models in real-world scenarios remains a significant challenge. The difficulty arises primarily from the inherent conflict between the need for sophisticated semantic reasoning and the constrained computational resources available on edge devices [Ghasemi *et al.*, 2024; Guo *et al.*, 2025].

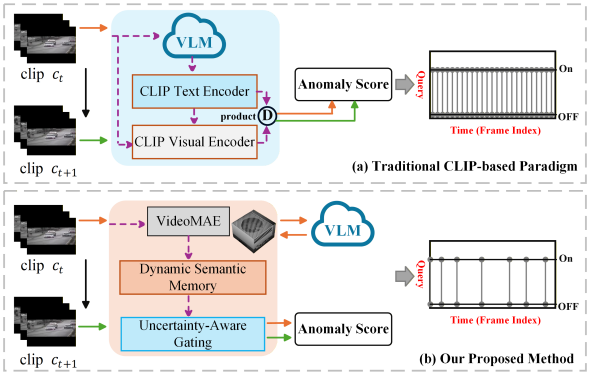

Figure 1: Comparison of different WSVAD paradigms. (a) Traditional methods suffer from high communication overhead due to per-clip VLM querying. (b) Our proposed framework reduces costs by querying the VLM only for uncertain and novel samples.

Traditional VAD approaches typically rely on reconstruction or prediction paradigms that operate under unsupervised or weakly supervised settings [Wu *et al.*, 2024b; Li *et al.*, 2025a]. The methods generally learn the distribution of normal patterns and treat deviations as anomalies. Although computationally efficient enough for some edge applications, they often struggle to distinguish between genuine anomalies and benign distributional shifts, such as dynamic background changes or camera jitter [Sultani *et al.*, 2018; Tian *et al.*, 2021]. Furthermore, the methods lack high-level semantic understanding, which restricts their ability to interpret complex scenes. Conversely, the emergence of Vision-Language Models (VLMs) has introduced a new paradigm where visual data is aligned with rich textual semantics through CLIP-based encoding [Deng *et al.*, 2025; Li *et al.*, 2025a]. VLMs demonstrate remarkable capability in zero-shot anomaly detection and semantic reasoning [Zanella *et al.*, 2024; Ye *et al.*, 2025; Shao *et al.*, 2025]. However, their massive parameter counts and heavy computational requirements render them unsuitable for direct deployment on resource-constrained edge hardware.

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To leverage the semantic power of VLMs without overwhelming edge resources, edge-cloud collaboration offers a promising direction [Zhang *et al.*, 2025]. A naive solution is to transmit all video data to a cloud-based VLM for processing [Kumar *et al.*, 2024; Wang *et al.*, 2025; Sharshar *et al.*, 2025]. Nevertheless, it incurs huge bandwidth costs and high latency, which are unacceptable for real-time surveillance applications[Khan *et al.*, 2022; Mondal *et al.*, 2024; Li *et al.*, 2025b]. Consequently, a critical research gap exists in developing a framework that can maintain the low latency of edge processing while selectively integrating the high-level semantic capabilities of cloud-resident large models.

To bridge the gap, we propose MemoVAD, a resource-efficient framework for video anomaly detection via dynamic semantic memory in edge computing scenarios. As shown in Fig. 1, anomalies typically exhibit recurring semantic patterns and manifest as temporally continuous segments. Therefore, continuous reliance on a heavy VLM is unnecessary. Instead, we introduce a novel collaborative mechanism where a lightweight edge detector handles the majority of the inference workload and queries the remote VLM only when necessary. Specifically, MemoVAD introduces three components to balance semantic capability and edge efficiency. First, it adopts a lightweight detector that uses a frozen VideoMAE [Tong *et al.*, 2022] backbone for motion feature extraction, together with a causal Temporal Context Encoder (TCE) to model local temporal dependencies. Second, we propose an Uncertainty-Aware Gating (UAG) mechanism grounded in Subjective Logic [Sensoy *et al.*, 2018], which estimates perceived uncertainty and triggers a VLM query when the edge model lacks sufficient evidence for a reliable decision. Finally, we develop a Dynamic Semantic Memory (DSM) that caches VLM-verified semantic prototypes on device. For semantically similar events, the model retrieves relevant knowledge from the memory instead of contacting the remote server, enabling efficient online knowledge distillation and progressively transferring VLM-level semantics to the edge model.

In summary, our main contributions are as follows:

- We propose MemoVAD, a resource-efficient collaborative framework that harmonizes the speed of edge computing with the semantic reasoning of large VLMs.
- We introduce an uncertainty-aware subjective-logic gate to query VLMs only under high perceived uncertainty, and a dynamic semantic memory caching VLM insights to cut communication overhead while preserving accuracy.
- Our MemoVAD demonstrates remarkable improvements compared to various benchmarks across two public datasets, validating its superior performance.

2 Related Works

2.1 Weakly Supervised Video Anomaly Detection with VLMs

Due to the huge cost of frame-level annotations, current research predominantly focuses on Weakly Supervised Video Anomaly Detection (WSVAD), where only video-level labels are available [Mishra *et al.*, 2024; Abdalla *et al.*, 2025; Liu *et al.*, 2024; Wu *et al.*, 2024a; Karim *et al.*, 2024; Zhang *et al.*, 2023; Pu *et al.*, 2024]. Multiple Instance Learning (MIL) serves as the dominant framework in the domain, treating videos as bags of clips to distinguish anomalous bags from normal ones [Zhang *et al.*, 2022; Tang *et al.*, 2023; Fang *et al.*, 2024]. However, standard MIL-based detectors typically rely on discriminative feature embeddings that lack explicit semantic interpretability. To mitigate the issue, recent studies have integrated Vision-Language Models (VLMs), leveraging the zero-shot capabilities of models like CLIP [Radford *et al.*, 2021] and GPT-4V to identify anomalies via textual prompting [Wu *et al.*, 2024b; Ye *et al.*, 2025; Yang *et al.*, 2024; Zanella *et al.*, 2024; Shao *et al.*, 2025]. While VLMs demonstrate superior performance in recognizing semantically complex events, their substantial computational overhead poses a significant barrier to real-time deployment. Our work builds upon the efficient MIL formulation but enhances it by integrating explicit semantic knowledge. Specifically, to mitigate the computational cost of VLMs, we adopt an online knowledge distillation strategy that continuously updates the edge model via a dynamic memory mechanism.

2.2 Efficient Edge-Cloud Collaboration

Deploying deep learning models on edge devices requires careful optimization to balance accuracy and efficiency [Guo *et al.*, 2025; Ghasemi *et al.*, 2024]. Common techniques include model compression methods such as quantization, pruning, and lightweight architecture design. While the techniques reduce inference latency, they often degrade model capacity and performance. Edge-cloud collaborative intelligence seeks to mitigate the issue by offloading heavy computation to the cloud [Zhang *et al.*, 2025; Shathik, 2025]. Traditional offloading strategies decide which parts of a model to execute locally and which to transmit based on bandwidth and battery constraints. However, most existing collaborative frameworks focus on partition points within a fixed network architecture rather than dynamic interaction based on sample difficulty. Our approach differs by employing an uncertainty-driven policy that dynamically determines the necessity of cloud interaction. By utilizing Subjective Logic to quantify evidence sufficiency, MemoVAD ensures that communication resources are expended only on hard and novel samples, thereby achieving a superior balance between resource efficiency and detection performance.

3 Methodology

3.1 Problem Definition

We formulate WSVAD as a Multiple Instance Learning (MIL) task. Let $\mathcal{X} = \{(\mathcal{V}_i, Y_i)\}_{i=1}^{|\mathcal{X}|}$ denote the training set, where $\mathcal{V}_i$ is an untrimmed video and $Y_i \in \{0, 1\}$ is the video-level label. $Y_i = 0$ indicates a normal video, while $Y_i = 1$ implies the video contains at least one anomalous event. Each video $\mathcal{V}_i$ is divided into a sequence of T non-overlapping clips $\{c_1, c_2, \ldots, c_T\}$.

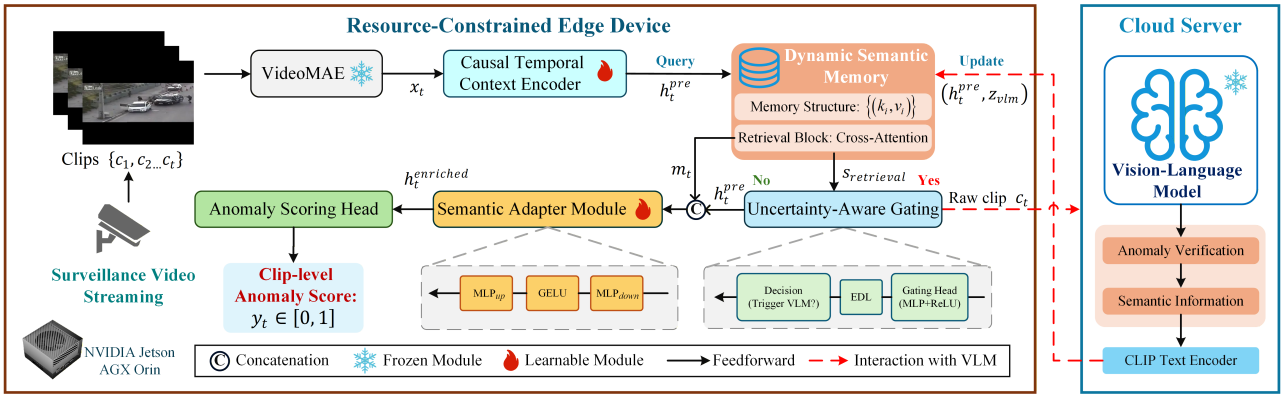


Figure 2: The architecture of the MemoVAD system.

The objective is to learn a clip-level anomaly scoring function $f_\theta(c_t) \to y_t \in [0,1]$, such that y_t is high for anomalous clips and low for normal ones. Under the MIL assumption, the relationship between clip scores and the video label is defined as:

$$Y_i = \max_{t=1}^{T} y_t. \tag{1}$$

Specifically, for a normal bag $Y_i = 0$, all clips are normal $y_t \approx 0$; for an anomalous bag $Y_i = 1$, at least one clip is anomalous $y_t \approx 1$.

Unlike traditional centralized VAD, we consider an edge-cloud collaborative scenario. The local edge device has limited computational resources and must minimize communication with the remote VLM. The goal is to maximize detection performance while adhering to a strict communication budget:

$$\min \sum_{t=1}^{T} \mathbb{I}(\text{Query}_t) \quad \text{s.t. Accuracy} \geq \delta, \tag{2}$$

where $\mathbb{I}(\cdot)$ is the indicator function for triggering a remote VLM query, and δ is the desired performance threshold.

3.2 Overview

We propose MemoVAD, a resource-efficient framework designed to bridge the gap between lightweight edge detection and semantic reasoning. As illustrated in Fig. 2, the framework operates under an edge-cloud collaborative paradigm to identify anomalies from the input video clips defined in Sec. 3.1. MemoVAD comprises three key components:

1. **Edge-Resident Detector:** A lightweight network utilizing a frozen VideoMAE backbone for initial feature extraction and temporal modeling.
2. **Uncertainty-Aware Gating (UAG):** A policy module that determines whether to query the VLM based on perceived uncertainty.
3. **Dynamic Semantic Memory (DSM):** A continuously updating memory bank that stores VLM-verified prototypes, enabling the edge model to retrieve high-level semantic knowledge without recurring communication costs.

3.3 Edge-Resident Network

Feature Extraction

To guarantee real-time inference on resource-constrained edge devices, we adopt VideoMAE-Small [Tong *et al.*, 2022] as our visual backbone. We freeze the pre-trained weights to preserve its generalizable motion features and prevent catastrophic forgetting during domain adaptation. Given an input video clip $c_t \in \mathbb{R}^{C \times F \times H \times W}$, the backbone extracts a compact feature vector x_t:

$$x_t = \mathcal{F}_{\text{backbone}}\ (c_t) \in \mathbb{R}^{D_{\text{stu}}}, \tag{3}$$

where D_{stu} denotes the feature embedding dimension. For the input preprocessing, we resize frames to a standard spatial resolution of $H \times W$ and sample F frames with a fixed temporal stride τ.

Causal Temporal Context Encoder

Since the backbone processes clips independently, the extracted feature x_t lacks temporal context required for detecting complex anomalies. To bridge the gap, we introduce a lightweight Temporal Context Encoder (TCE) implemented as a 2-layer causal Transformer Encoder, which aggregates information from a fixed-length history window of L clips. To retain sequential order information, learnable positional embeddings are added to the input sequence before encoding:

$$h_t^{\text{pre}} = \text{TCE}_{\text{causal}}\ ([x_{t-L+1}, \ldots, x_t] + P), \tag{4}$$

where P denotes learnable positional embeddings. The output $h_t^{\text{pre}} \in \mathbb{R}^{D_{\text{stu}}}$ is the pre-enrichment contextual student feature for clip t. In deployment, we implement the causal Transformer with KV-cache for streaming inference, enabling amortized constant-time updates per incoming clip.

3.4 Dynamic Semantic Memory (DSM)

DSM is designed to realize *online knowledge distillation* by caching VLM reasoning results and enabling semantic retrieval on the edge.

Memory Structure

We structure the memory as a set of key-value pairs $\mathcal{M} = \{(k_i, v_i)\}_{i=1}^{N}$ with memory size N.

- **Key** $k_i \in \mathbb{R}^{D_{\text{stu}}}$ stores the pre-enrichment student feature h^{pre} for a VLM-confirmed event. It ensures that keys share the same distribution as incoming queries.
- **Value** $v_i \in \mathbb{R}^{D_{\text{vlm}}}$ stores the corresponding semantic embedding produced by the teacher VLM, serving as high-level knowledge to be distilled.

Memory Retrieval

For each incoming clip feature h_t^{pre}, we retrieve relevant semantic information from $\mathcal{M}$ using multi-head cross-attention. The query is derived from the student feature, while the memory keys and values serve as K and V:

$$Q = h_t^{\text{pre}} W_Q, \quad K = \mathcal{M}_{\text{key}} W_K, \quad V = \mathcal{M}_{\text{val}} W_V. \tag{5}$$

The retrieved semantic information m_t is computed via the attention mechanism:

$$m_t = \text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V. \tag{6}$$

Simultaneously, to quantify retrieval confidence for gating, we compute the maximum cosine similarity between h_t^{pre} and stored keys:

$$s_{\text{retrieval}} = \max_{i \in \{1,\dots,N\}} \left(\frac{h_t^{\text{pre}} \cdot k_i}{\|h_t^{\text{pre}}\|_2 \|k_i\|_2}\right) \in [-1, 1]. \tag{7}$$

The metric $s_{\text{retrieval}}$ measures how well the current input matches the known anomalous prototypes in the memory.

Semantic Adapter Module (SAM)

Directly fusing semantic prototypes into the student space may cause distribution mismatch. We introduce a lightweight Semantic Adapter Module (SAM) to align and fuse m_t into the student feature space.

We first project the retrieved semantic prototype to the student dimension via a lightweight projection $\phi : \mathbb{R}^{D_{\text{vlm}}} \to \mathbb{R}^{D_{\text{stu}}}$ (e.g., a single linear layer). Then we concatenate and pass through a bottleneck adapter:

$$\Delta h_t = \text{MLP}_{up}\left(\sigma\left(\text{MLP}_{down}\left(\text{Concat}\left[h_t^{\text{pre}}, \phi(m_t)\right]\right)\right)\right), \tag{8}$$

where MLP_{down} compresses by ratio $r = 4$, σ is GELU, and MLP_{up} restores to D_{stu}. The enriched student feature is obtained by a gated residual connection:

$$h_t^{\text{enriched}} = \text{LayerNorm}\left(h_t^{\text{pre}} + \alpha \cdot \Delta h_t\right), \tag{9}$$

where α is a learnable scalar initialized to 0 to prevent negative transfer in early training.

3.5 Uncertainty-Aware Gating (UAG)

Continuous VLM querying is extremely expensive. UAG requests VLM assistance only for *hard or novel* samples, using perceived uncertainty and memory confidence.

Gating Policy

Softmax confidence cannot reliably separate aleatoric and perceived uncertainty. We adopt Subjective Logic [Sensoy *et al.*, 2018] to estimate perceived uncertainty via evidential learning.

Given the pre-enrichment feature h_t^{pre}, the gating head predicts non-negative evidence:

$$\mathbf{e}_t = \text{ReLU}\left(\text{MLP}\left(h_t^{\text{pre}}\right)\right), \quad \mathbf{e}_t = [e_{t,0}, e_{t,1}], \tag{10}$$

for the Normal and Anomalous classes. Evidence defines a Dirichlet distribution $\text{Dir}(\boldsymbol{\alpha}_t)$:

$$\boldsymbol{\alpha}_t = \mathbf{e}_t + \mathbf{1}, \quad S_t = \sum_k \alpha_{t,k}, \tag{11}$$

where S_t represents evidence strength. The perceived uncertainty is defined as inverse total evidence:

$$u_t = \frac{K}{S_t} = \frac{2}{\alpha_{t,0} + \alpha_{t,1}}, \quad (K = 2). \tag{12}$$

To improve robustness under domain shift where models can be over-confident yet wrong, we trigger VLM queries when the case is uncertain and novel. The triggering condition is:

$$\text{Trigger}_t = \mathbb{I}\left(u_t > \tau_{\text{unc}} \wedge s_{\text{retrieval}} < \tau_{\text{sim}}\right), \tag{13}$$

where $\tau_{\text{unc}}, \tau_{\text{sim}}$ are hyper-parameters trading off accuracy and communication cost.

VLM Inference and Memory Update

When triggered, the raw clip c_t is transmitted to the remote VLM. We uniformly sample F frames from c_t and provide a lightweight prompt for anomaly verification. The VLM outputs: (1) Anomaly Verification, deciding whether the clip truly contains an anomaly; and (2) Semantic Extraction, producing a text-aligned embedding $z_{\text{vlm}} \in \mathbb{R}^{D_{\text{vlm}}}$.

If the VLM confirms an anomaly, we write the new knowledge into memory:

$$\mathcal{M} \leftarrow \mathcal{M} \cup \left\{\left(h_t^{\text{pre}}, z_{\text{vlm}}\right)\right\}. \tag{14}$$

Online Semantic-Diversity Replacement. To keep a fixed memory budget $N_{\max}$ while avoiding quadratic recomputation, we maintain a redundancy score for each key:

$$\rho_i = \max_{j \neq i} \cos(k_i, k_j). \tag{15}$$

When inserting a new key k_{new}, we compute $\cos(k_{\text{new}}, k_i)$ for all stored keys and update affected ρ_i incrementally. If the memory is full, we remove the most redundant key $\arg\max_i \rho_i$, yielding an online replacement with amortized $O(ND_{\text{stu}})$ per insertion.

3.6 Objective Function

The model is trained with weak video-level labels. Let $S(\cdot)$ denote the anomaly classifier head followed by a Sigmoid. The predicted anomaly score for the t-th clip is:

$$y_t = S\left(h_t^{\text{enriched}}\right) \in [0, 1]. \tag{16}$$

MIL Ranking Loss

We formulate weakly supervised VAD as a Multiple-Instance Learning task. Normal videos are negative bags $\mathcal{B}_n$ and anomalous videos are positive bags $\mathcal{B}_a$. Using the standard MIL assumption, the video-level score is represented by the maximum clip score. The ranking loss is:

$$\mathcal{L}_{\text{mil}} = \max\left(0, m - \max_{t \in \mathcal{B}_a} y_t + \max_{t \in \mathcal{B}_n} y_t\right), \tag{17}$$

where $m \in (0, 1)$ is the margin hyperparameter.

Semantic Distillation Loss

To distill semantic knowledge from the VLM, we minimize the distance between student and teacher representations. We introduce a projection head $\psi : \mathbb{R}^{D_{\text{stu}}} \to \mathbb{R}^{D_{\text{vlm}}}$ (two-layer MLP) and apply supervision only when teacher signals are available. The distillation loss is:

$$\mathcal{L}_{\text{distill}} = \frac{1}{\sum_{t=1}^{T} \mathbb{M}_t + \epsilon} \sum_{t=1}^{T} \mathbb{M}_t \cdot \| \psi \left(h_t^{\text{enriched}} \right) - \text{stop\_grad} \left(z_{vlm} \right) \|_2^2, \tag{18}$$

where ϵ is a small constant for numerical stability. Here, $\mathbb{M}_t = 1$ if the VLM is triggered for clip t, and 0 otherwise. The stop-gradient operator treats the VLM as a fixed semantic anchor.

Temporal Smoothness Loss

We impose temporal continuity and sparsity priors:

$$\mathcal{L}_{\text{smooth}} = \sum_{t=1}^{T-1} \left(y_t - y_{t+1} \right)^2 + \lambda_{sp} \sum_{t=1}^{T} y_t, \tag{19}$$

where the first term enforces smoothness, and the second encourages sparsity of anomaly predictions. λ_{sp} is a sparsity hyper-parameter that balances the two constraints. It prevents the trivial solution where the model predicts high scores for all clips.

Gating Head Supervision

We supervise the evidential gating head following Evidential Deep Learning [Sensoy *et al.*, 2018]. Let $Y_{\text{bag}} \in \{0, 1\}$ be the video-level label. To reduce label noise under MIL, we apply the loss only to the top-scoring clip(s) in each bag:

$$\mathcal{L}_{\text{gate}} = \mathcal{L}_{\text{EDL}}(\boldsymbol{\alpha}_t, Y_{\text{bag}}). \tag{20}$$

Total Loss

The final objective function is a weighted sum of the components:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{mil}} + \lambda_1 \mathcal{L}_{\text{distill}} + \lambda_2 \mathcal{L}_{\text{smooth}} + \lambda_3 \mathcal{L}_{\text{gate}}, \tag{21}$$

where λ_1, λ_2, and λ_3 are pre-defined hyperparameters that balance the trade-off between anomaly detection, semantic alignment, and uncertainty estimation.

4 Experiments

4.1 Experimental Settings

Datasets. We evaluate MemoVAD on two large-scale weakly supervised video anomaly detection benchmarks. **(1) UCF-Crime** [Sultani *et al.*, 2018] contains 1,900 real-world surveillance videos spanning 13 anomaly categories and normal activities. **(2) XD-Violence** [Wu *et al.*, 2020] consists of 4,754 videos collected from movies and games, providing audio-visual signals. In our experiments, we use only the visual modality.

Metrics. Following standard protocols, we employ the Area Under the Receiver Operating Characteristic Curve (**AUC**) for UCF-Crime and Average Precision (**AP**) for XD-Violence to evaluate detection performance. In addition to detection performance, we strictly evaluate resource efficiency in edge scenarios. Specifically, we report Throughput (**FPS**) and Latency (**s**) to verify real-time capabilities, and define Communication Rate (**CR**) as the percentage of clips that trigger a VLM query.

Baselines. For comparison, Sultani et al. [Sultani *et al.*, 2018], RTFM [Tian *et al.*, 2021], CRFD [Wu and Liu, 2021], MSL [Li *et al.*, 2022], MGFN [Chen *et al.*, 2023], UR-DMU [Zhou *et al.*, 2023], CLIP-TSA [Joo *et al.*, 2023], TPWNG [Yang *et al.*, 2024], VadCLIP [Wu *et al.*, 2024b], OVVAD [Li *et al.*, 2025a], and EventVAD [Shao *et al.*, 2025] are chosen as baselines.

Method	Ref.	Backbone	AUC (%)↑	AP (%)↑
Sultani et al.	CVPR'18	C3D	77.92	73.20
RTFM	ICCV'21	I3D	84.30	77.81
CRFD	TIP'21	I3D	84.89	75.90
MSL	AAAI'22	I3D	85.62	78.58
MGFN	AAAI'23	I3D	86.67	80.11
UR-DMU	AAAI'23	I3D	86.97	81.66
CLIP-TSA	ICIP'23	CLIP	87.58	82.17
TPWNG	CVPR'24	CLIP	87.79	83.68
VadCLIP	AAAI'24	CLIP	88.02	84.51
OVVAD	CVPR'25	CLIP	86.40	69.31
EventVAD	MM'25	CLIP	87.51	64.04
MemoVAD (Ours)	-	VideoMAE-S	**89.45**	**85.97**

Table 1: Comparison results on UCF-Crime (AUC) and XD-Violence (AP). Best results are highlighted in **bold**.

Method	FPS ↑	Latency (s)↓	CR_{UCF}(%)↓	CR_{XD}(%)↓
I3D baseline	23.7	0.868	0.00	0.00
CLIP-based baseline	11.5	1.512	100.0	100.0
MemoVAD (Ours)	**36.2**	**0.475**	**8.63**	**15.72**

Table 2: Efficiency on Jetson AGX Orin (streaming, batch=1). FPS and Latency are measured end-to-end. CR: Percentage of clips querying the remote VLM.

4.2 Comparison with State-of-the-Art Methods

Main Results. As presented in Table 1, MemoVAD achieves 89.45% AUC on UCF-Crime and 85.97% AP on XD-Violence, consistently outperforming prior approaches with C3D/I3D or CLIP-based feature backbones. Such consistent gains across two widely-used benchmarks indicate the strong effectiveness and robustness of our method under different anomaly categories and evaluation metrics. In particular, MemoVAD improves the best competitors TPWNG and VadCLIP by an absolute margin of 1.66% and 1.43% AUC on UCF-Crime, and 2.29% and 1.46% AP on XD-Violence, respectively. Notably, the gains are achieved by utilizing the frozen VideoMAE-S as a resource-efficient student backbone, demonstrating that accurate anomaly detection does not strictly require computationally intensive foundation models.

Efficiency Results. MemoVAD is explicitly designed for real-time anomaly detection under an edge-collaborative set-

TCE	DSM	UAG	SAM	AUC (%)↑	FPS ↑	Latency (s)↓	CR (%)↓
×	×	×	×	72.33	40.6	0.266	0.00
✓	×	×	×	79.56	39.8	0.353	0.00
✓	✓	×	×	90.10	12.8	1.481	100.0
✓	✓	✓	×	87.85	37.5	0.462	8.63
✓	✓	✓	✓	**89.45**	**36.2**	**0.475**	**8.63**

Table 3: Ablation study of key components on UCF-Crime. ✓ and × denote the inclusion and exclusion of each module, respectively.

Gating Strategy	Metric	AUC (%)↑	CR (%)↓
Softmax Entropy	Confidence	86.12	12.45
Evidential Uncertainty (Only)	Uncertainty	87.05	9.80
Retrieval Similarity (Only)	Similarity	88.20	14.20
Hybrid (Ours)	Unc. + Sim.	**89.45**	**8.63**

Table 4: Comparison of different gating policies on UCF-Crime.

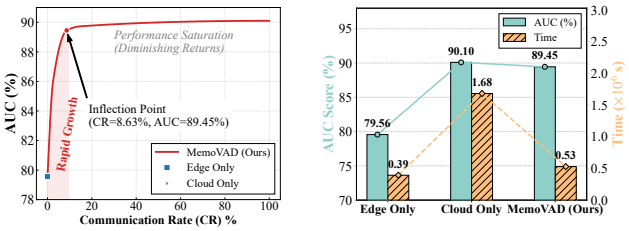
ting, where both on-device computation and communication costs are critical. As detailed in Table 2, MemoVAD maintains real-time capability on the Jetson AGX Orin by achieving a throughput of 36.2 FPS. The performance represents a substantial improvement over the I3D baseline, which operates exclusively on the edge at 23.7 FPS. Furthermore, MemoVAD significantly outpaces the CLIP-based baseline that relies continuously on remote VLM support, running at only 11.5 FPS. The throughput improvement is also reflected in the latency metrics, where MemoVAD achieves a rapid response time of 0.475 seconds, markedly outperforming both the CLIP-based baseline and the I3D-based baseline. Such a performance gain validates the efficacy of utilizing the lightweight VideoMAE-S architecture, which avoids the computational bottlenecks often associated with the heavier semantic backbones employed by competing methods. Beyond local computational efficiency, MemoVAD significantly minimizes the dependency on remote VLM access. While the CLIP-based baseline necessitates a 100% query rate to function, our method initiates VLM queries for merely 8.63% and 15.72% of the clips on the UCF-Crime and XD-Violence datasets respectively. By processing the vast majority of clips locally, MemoVAD effectively circumvents the bandwidth limitations and latency penalties often associated with expensive remote inference.

4.3 Ablation Studies

Effectiveness of Key Components. Table 3 summarizes the incremental contributions of each module. Starting with the baseline in Row 1, the frozen VideoMAE backbone achieves 72.33% AUC at 40.6 FPS, but is constrained by the lack of temporal modeling. Incorporating the causal TCE as shown in Row 2 effectively aggregates historical motion cues and boosts AUC to 79.56% with a negligible latency overhead resulting in 39.8 FPS. To gauge the maximum potential of semantic reasoning, we evaluate a teacher forcing variant with DSM in Row 3 that queries the VLM for every clip. While the configuration yields a peak AUC of 90.10%, it incurs huge costs including a 100% communication rate and

Update Policy	AUC (%)↑	AP (%)↑
First-In-First-Out (FIFO)	87.34	83.10
Random Replacement	86.90	82.55
Least Recently Used (LRU)	88.10	84.20
Semantic-Diversity (Ours)	**89.45**	**85.97**

Table 5: Ablation on memory update policies. AUC and AP are selected as metrics.



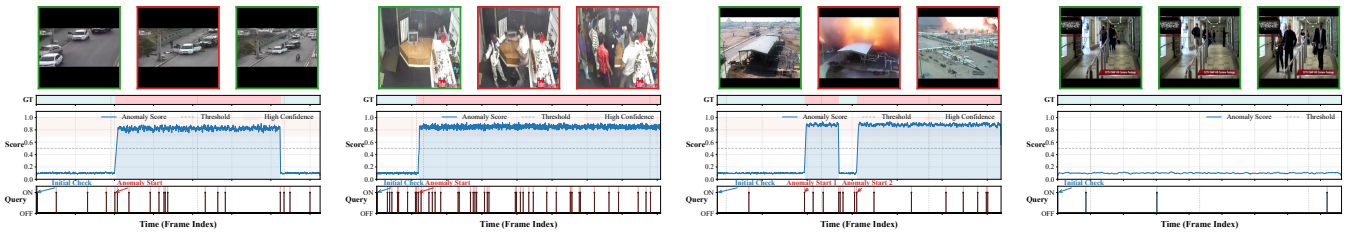
(a) (b)

Figure 3: Trade-off evaluation on UCF-Crime. (a) AUC vs. Communication Rate. (b) AUC vs. Time

a throughput drop to 12.8 FPS with a high latency of 1.481 seconds, which renders it impractical for edge deployment. To mitigate the issue, the UAG mechanism in Row 4 selectively triggers queries only for clips with high-uncertainty and novelty, reducing communication to 8.63% and restoring a real-time throughput of 37.5 FPS with 0.462 seconds, while incurring only a modest AUC drop to 87.85%. Finally, the introduced SAM alleviates the feature distribution mismatch between the student and teacher. By aligning retrieved semantics, it recovers the AUC to 89.45% and closely matches the upper bound while maintaining a high efficiency of 36.2 FPS and a marginal latency of 0.475 seconds.

Analysis of Gating Policies. To validate the design of our Uncertainty-Aware Gating, we compare the proposed method against standard baselines as detailed in Table 4. The baseline utilizing solely Softmax confidence yields suboptimal performance of 86.12%, primarily due to its inability to discriminate between hard samples and out-of-distribution data. While employing evidential uncertainty alone improves precision, it fails to capture novel semantic events that are statistically confident yet semantically unfamiliar. Consequently, our hybrid approach achieves the optimal synergy by triggering VLM queries exclusively when the model exhibits perceived uncertainty or when the input remains semantically distinct from existing memory prototypes.

Effectiveness of Memory Dynamics. We further investigate the impact of memory management on long-term learning stability in Table 5. Naive strategies, such as FIFO or Random replacement, result in the catastrophic forgetting of rare anomaly prototypes, leading to a performance degradation exceeding 2%. In contrast, our Online Semantic-Diversity Replacement ensures the retention of a spanning set of diverse abnormal information, thereby maximizing the utility of the fixed storage budget of 2,048 slots.



(a) Arrest (b) Assault (c) Explosion (d) Normal Video

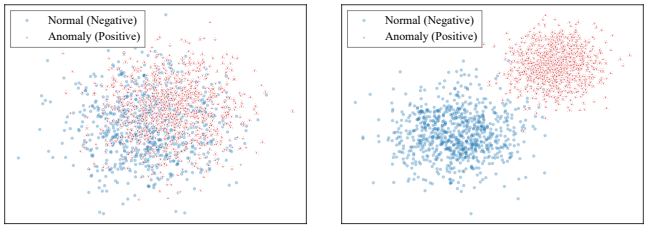
Figure 4: Qualitative visualization of MemoVAD on abnormal and normal scenarios. The rows from top to bottom illustrate: input frames with detection status (Green: Normal, Red: Anomaly), Ground Truth (GT), predicted Anomaly Score, and the VLM Query Trigger signal.

Efficiency-Accuracy Trade-off. Fig. 3 illustrates the balance between computational efficiency and detection accuracy. To characterize the operational envelope of MemoVAD, we systematically modulate the gating hyperparameters, specifically the uncertainty threshold τ_{unc} and the similarity threshold τ_{sim}. Fig. 3a reveals a smooth Pareto frontier where the proposed method maintains an AUC exceeding 89% even when the communication overhead is constrained to less than 10%. Furthermore, we also provide a comparative analysis against the baseline deployment paradigms in Fig. 3b. Specifically, while exhibiting a marginal degradation in AUC compared to the Cloud-only approach, our method significantly reduces the inference latency. Notably, the total runtime of MemoVAD is approximately one-third of that required by the Cloud-only paradigm, demonstrating its practicality for real-time edge computing scenarios. Such performance significantly surpasses the baselines and underscores the adaptability of our framework to fluctuating network bandwidths in real-world deployments.

4.4 Qualitative Analysis

Qualitative Visualization. Fig. 4 details the inference dynamics of MemoVAD across diverse scenarios. The blue curves denote the predicted anomaly scores and the black vertical stems indicate VLM query triggers. As presented in Fig. 4a, the query frequency spikes immediately at the anomaly onset to resolve high perceived uncertainty. Upon the termination of the event, the system rapidly validates the return to a normal state, resulting in a rapid decay of the anomaly score. Similarly, in Fig. 4b, where the anomaly persists until the end of the video, the system maintains robust recognition throughout the abnormal event duration. Notably, in Fig. 4c, the MemoVAD successfully validates the interval between events to confirm the temporary restoration of normality, demonstrating its ability to capture complex temporal dependencies. In the normal video depicted in Fig. 4d, our system maintains consistently low anomaly scores with extremely sparse updates, effectively minimizing computational costs in the absence of semantic shifts. Overall, MemoVAD precisely localizes events matching ground-truth red borders, while meeting rate limits via content-adaptive resources.

Feature Discrimination Visualization. To intuitively evaluate the quality of learned representations, we visualize the feature distributions on the UCF-Crime dataset using t-SNE, as depicted in Fig. 5. The visualization in Fig. 5a reveals that the baseline VideoMAE exhibits a high degree of feature entanglement, where anomalous samples are heavily overlapped with normal patterns due to the lack of discriminative semantic guidance. In contrast, as illustrated in Fig. 5b, benefiting from specific optimization and semantic enrichment of MemoVAD, the learned features form distinct and compact clusters with clear decision boundaries. It further demonstrates that MemoVAD effectively disentangles anomalous features away from the normal distribution.



(a) Pre-enrichment Features (b) Enriched Features

Figure 5: Feature visualization via t-SNE on UCF-Crime dataset.

5 Conclusion

In this work, we proposed MemoVAD, a framework that strategically bridges a lightweight edge detector with a powerful remote VLM. Instead of continuously relying on the cloud, our system learns to seek remote guidance only when uncertain, caching the insights locally to improve over time. Our experiments confirm that the uncertainty-driven collaboration yields state-of-the-art performance with minimal bandwidth usage, demonstrating a practical path for deploying foundation model capabilities in real-world surveillance without being overwhelmed by their computational weight.

Future work will explore extending the paradigm to collaborative edge computing scenarios, where distributed devices can share semantic knowledge and jointly maintain memory. We will also investigate long-term adaptation under non-stationary environments, including scene shifts and evolving anomaly patterns. In addition, more robust memory update and validation mechanisms will be studied to reduce the influence of noisy VLM feedback while preserving the efficiency benefits of selective remote querying.

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