

# VADTree: Explainable Training-Free Video Anomaly Detection via Hierarchical Granularity-Aware Tree



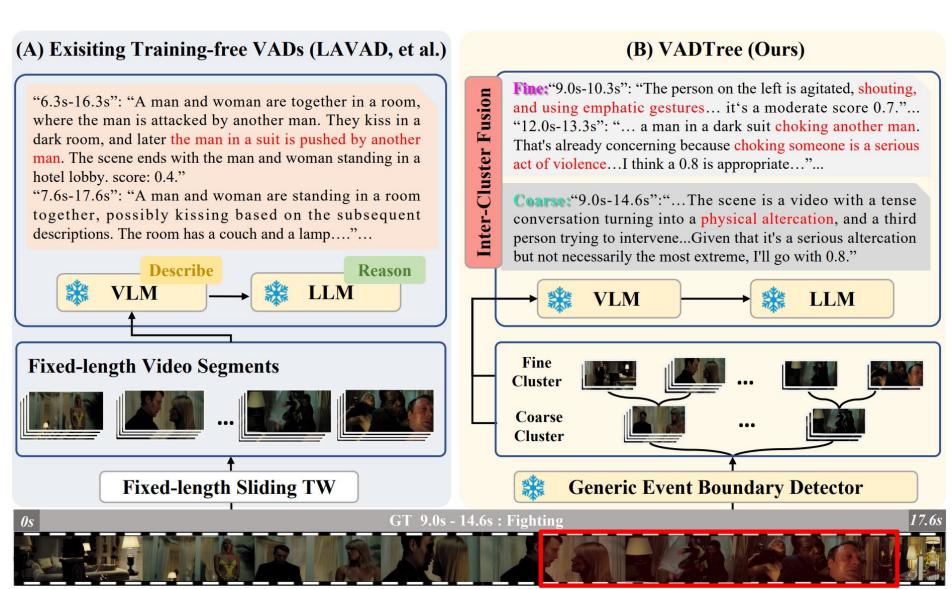




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### Introduction

- 1. Key Challenges in Video Anomaly Detection
- > Fixed-Length Sampling Limitation: Clash with variable anomaly durations, causing misalignment. and discontinuity.
- > Complex Event Modeling Gap: Conflicts between temporal scales hinder contextual reasoning for extended anomalies.



2. Core Contributions

VADTree(Ours)

Method

RTFM [37]

MGFN [4]

TEVAD [3]

GS-MoE [7

 $\pi$ -VAD [26]

UR-DMU [26]

**VADTree (Ours)** 

- > VADTree: Tree structure driven video anomaly detection.
- ➤ Hierarchical Granularity-Aware Tree (HGTree):

Constructs multi-granularity event nodes from pre-trained

84.74

 $AUC_a$  (%)

67.95

69.54

71.25

67.85

68.26

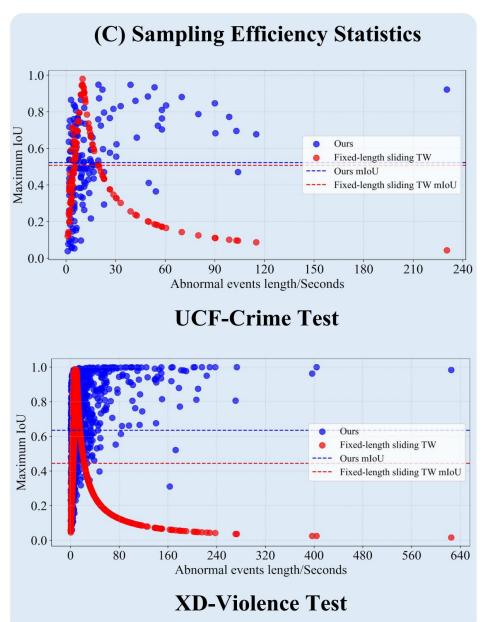
71.41

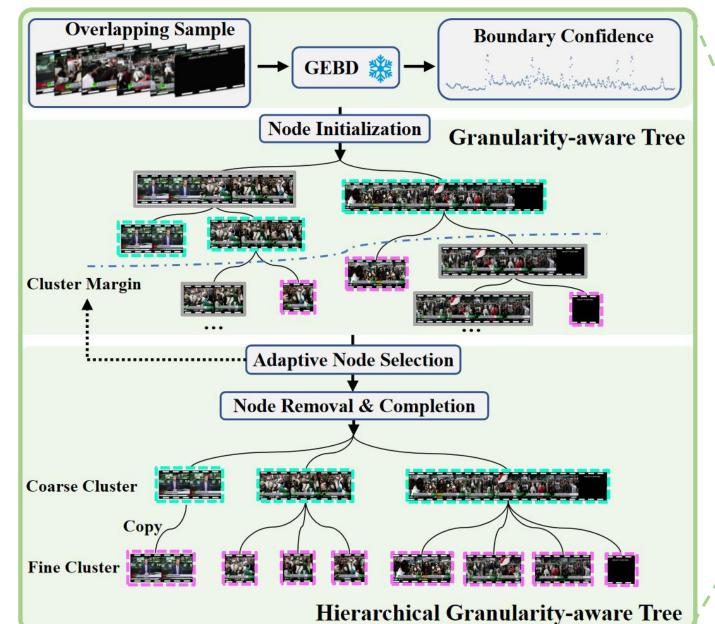
77.86

75.49

knowledge for robust representation.

# **Hierarchical Granularity-Aware Tree**

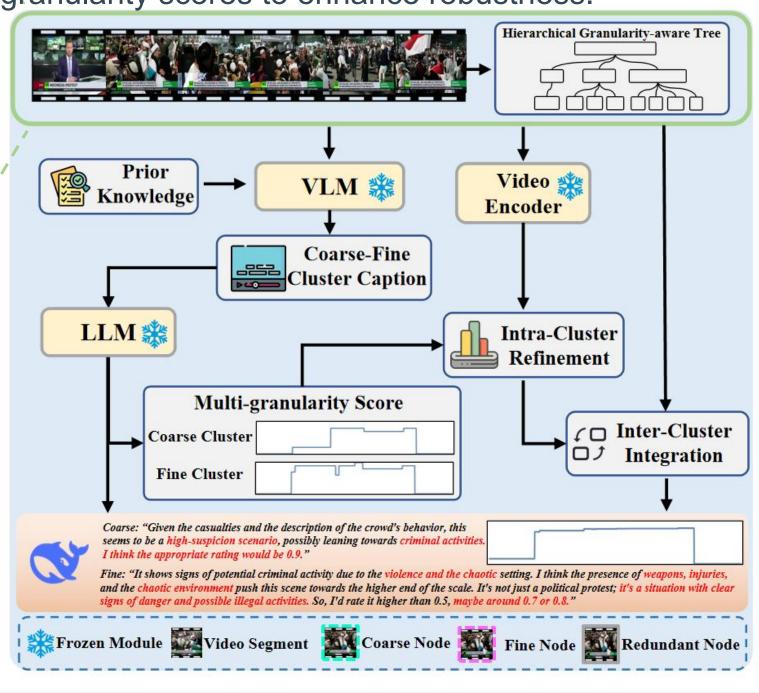




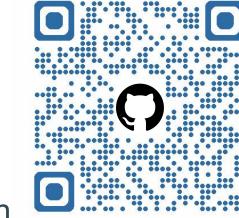
- > Segmentation Confidence Sequence: Based on pre-trained GEBD model and overlapping sampling.
- > Generic Event Node Initialization: Depth first traversal for representation initialization.
- > Adaptive Node Stratification: Maximization of inter-hierarchical event confidence divergence via K-Means, RemoveDup, and Complete.
- > Sampling Efficiency Statistics: Our sampling method more effectively captures anomalous events of varying lengths and generates fewer segments.

### **VADTree**

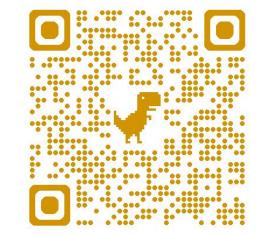
- > Prior-infused Node Scoring: Injecting prior knowledge to enhance anomaly perception.
- > Intra-cluster Node Refinement: Refine scoring through intra cluster similarity.
- ➤ Inter-cluster Node Correlation: Integrating multigranularity scores to enhance robustness.



**Qualitative Results** 







Paper



WeChat

# **Experiments Results**

#### **UCF-Crime dataset (AUC)**

|                           | •                   |       |  |  |
|---------------------------|---------------------|-------|--|--|
| Explainable VAD Methods   |                     |       |  |  |
| VADor [24]                | Fine-tuning         | 88.13 |  |  |
| Holmes-VAD [59]           | Fine-tuning         | 89.51 |  |  |
| Holmes-VAU [60]           | Fine-tuning         | 88.96 |  |  |
| VERA [50]                 | Verbalized Learning | 86.55 |  |  |
| Blip2 [18]                | Training-free       | 46.42 |  |  |
| ZS CLIP [27]              | Training-free       | 53.16 |  |  |
| ZS ImageBind (Image) [12] | Training-free       | 53.65 |  |  |
| ZS ImageBind (Video) [12] | Training-free       | 55.78 |  |  |
| LLaVA-1.5 [20]            | Training-free       | 72.84 |  |  |
| Video-Llama2 [58]         | Training-free       | 74.42 |  |  |
| LAVAD [55]                | Training-free       | 80.28 |  |  |
| SUVAD [11]                | Training-free       | 83.90 |  |  |
| MCANet [9]                | Training-free       | 82.47 |  |  |
| EventVAD [30]             | Training-free       | 82.03 |  |  |

**Supervision** 

Weakly Supervised

Weakly Supervised

Weakly Supervised

Weakly Supervised

Weakly Supervised

Weakly Supervised

Training-free

Training-free

**MSAD** dataset

86.65

84.96

86.82

85.78

#### XD-Violence dataset (AP & AUC)

| ND-VIOICIICO              | dataset (Al         | a Au  | O)    |
|---------------------------|---------------------|-------|-------|
| Expl                      | ainable VAD Methods |       |       |
| Holmes-VAD [59]           | Fine-tuning         | 90.67 | -     |
| Holmes-VAU [60]           | Fine-tuning         | 87.68 | -     |
| VERA [50]                 | Verbalized Learning | 70.54 | 88.26 |
| Blip2 [18]                | Training-free       | 10.89 | 29.43 |
| ZS CLIP [27]              | Training-free       | 17.83 | 38.21 |
| ZS ImageBind (Image) [12] | Training-free       | 27.25 | 58.81 |
| ZS ImageBind (Video) [12] | Training-free       | 25.36 | 55.06 |
| LLaVA-1.5 [20]            | Training-free       | 50.26 | 79.62 |
| Video-Llama2 [58]         | Training-free       | 53.57 | 80.21 |
| LAVAD [55]                | Training-free       | 62.01 | 85.36 |
| SUVAD [11]                | Training-free       | 70.10 | -     |
| MCANet* [9]               | Training-free       | 69.72 | 87.43 |
| EventVAD [30]             | Training-free       | 64.04 | 87.51 |
| VADTree (Ours)            | Training-free       | 67.82 | 90.44 |
| VADTree* (Ours)           | Training-free       | 68.85 | 90.55 |

**HGTree Ablation**  $AP(\%) AP_a(\%)$ **AUC** (%) **Cluster Tool** Clusters 80.89 Fine 82.81 Fine 80.85 75.30 K-Means Coarse + Fine 76.68 0.4K-Means Coarse + Fine

Coarse + Fine

Coarse + Fine

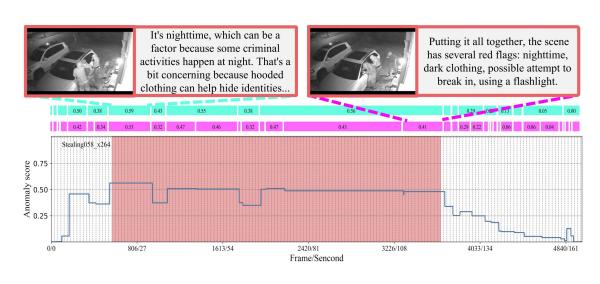
K-Means

- > Comparison with SOTA: Surpassing the best training-free methods. Significantly outperforms weakly supervised methods on MSAD.
- > Ablation Study: Hierarchical structure brings robust performance gains. Prior information effectively enhances anomaly perception.
- > Qualitative Results: VADTree exhibits a superior ability to capture multi-granularity anomalies.

#### **VADTree Ablation**

| <b>Todule</b>                  | AUC (%) |
|--------------------------------|---------|
| IGTree Fine Cluster            | 71.57   |
| Prior-infused Node Scoring     | 75.67   |
| Intra-cluster Node Refinement  | 83.05   |
| Inter-cluster Node Correlation | 84.74   |





## β parameter experiment of correlation

