VERUS-INSIGHT: TOWARDS EXPLAINABLE ARTIFACT DETECTION IN AI-GENERATED VIDEOS

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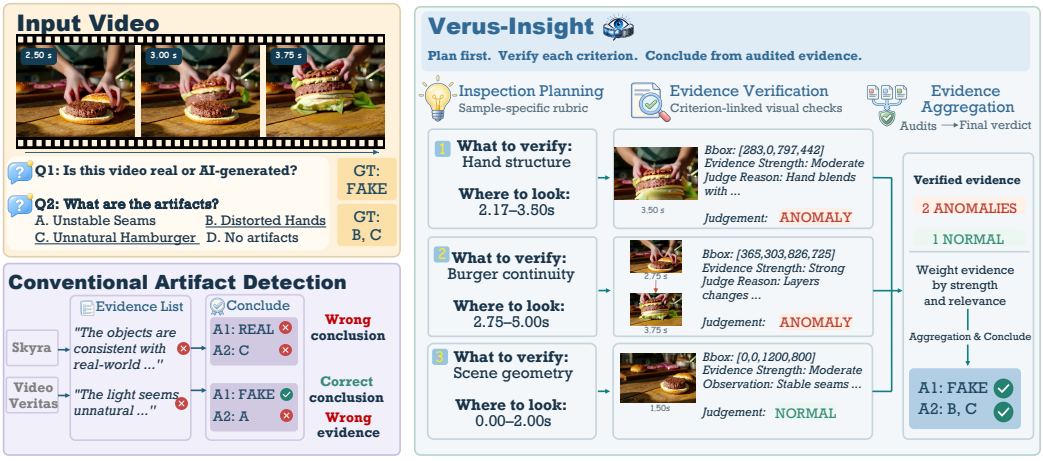

Figure 1: **Towards explainable and reliable AI-generated video detection.** Conventional artifact detectors may make incorrect source predictions or reach the correct conclusion with inaccurate artifact evidence. Verus-Insight instead performs *Inspection Planning*, *Evidence Verification*, and *Evidence Aggregation*, grounding source decisions in explicitly verified, human-perceivable artifact evidence for more explainable and reliable detection.

ABSTRACT

Recent advances in video generation have made synthetic videos increasingly realistic, placing greater demands on reliable AI-generated video detection. Existing artifact-based detectors typically identify generation artifacts as evidence for source prediction, yet they may either fail to recognize subtle artifacts or reach the correct source decision without faithfully identifying the evidence underlying it. In this work, we systematically investigate how to design and train effective artifact detectors and formulate artifact detection as a structured process comprising three complementary capabilities: *Inspection Planning*, which determines what should be examined; *Evidence Verification*, which verifies whether the inspected content exhibits genuine generation artifacts; and *Evidence Aggregation*, which integrates the verified evidence into the final source decision. Building on this formulation, we introduce **Verus-Insight**, trained with human-anchored full-process supervision and progressive capability training to strengthen both fine-grained artifact detection and video-level detection. We further introduce **Verus-Bench**, a benchmark with fine-grained human annotations of perceptible artifacts for evaluating artifact detection. Extensive experiments across diverse benchmarks demonstrate that Verus-Insight achieves strong performance in both fine-grained artifact analysis and AI-generated video detection, with substantial gains in recovering human-perceived artifacts. Further analyses reveal that the three capabilities are complementary yet distinct, and that Verus-Insight more reliably converts relevant inspection targets into supported artifact evidence without increasing spurious artifact claims.

1 INTRODUCTION

Recent advances in video generation (Google, 2025; Kuaishou AI Team, 2024; Wan et al., 2025) have substantially improved the realism and diversity of synthetic videos, making them increasingly

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difficult to distinguish from real ones. Reliable AI-generated video detection has therefore become important for applications such as content authenticity verification, generation quality evaluation, and provenance and safety analysis (Tang et al., 2026). A prevailing approach is to identify generation artifacts as evidence for source determination, with recent methods increasingly leveraging multimodal large language models (MLLMs) to recognize such artifacts and determine whether a video is real or AI-generated (Li et al., 2025; Tan et al., 2026; Wen et al., 2025).

Despite this progress, existing detectors still struggle to reliably identify the specific artifacts present in a video. They may overlook subtle spatiotemporal abnormalities or mistake normal visual phenomena for generation artifacts (Li et al., 2025), while coarse or superficial analysis can further limit their ability to recognize concrete generation errors (Tan et al., 2026). As illustrated in Figure 1, even a correct source prediction can accompany inaccurate or incomplete artifact identification. These failures limit the usefulness of detectors for diagnosing specific problems in generated videos. Reliable artifact detection therefore requires targeted inspection of the video content and careful discrimination between genuine abnormalities and normal observations. This motivates training detectors to identify what should be checked in each video and determine, from the corresponding visual evidence, whether an artifact is actually present.

To address these limitations, we systematically investigate how to design and train effective artifact detectors for AI-generated videos. As illustrated in Figure 1, we formulate artifact detection as a structured process comprising three complementary stages: *Inspection Planning*, which determines what to examine; *Evidence Verification*, which verifies whether the inspected content exhibits generation artifacts; and *Evidence Aggregation*, which integrates the verified evidence into the final source decision. This decomposition allows us to explicitly examine and strengthen the capabilities underlying the detection process. Building on this formulation, we introduce **Verus-Insight**, trained with human-anchored full-process supervision and progressive capability training to improve both fine-grained artifact identification and video-level source detection. We further introduce **Verus-Bench**, a benchmark with fine-grained human annotations of perceptible artifacts for evaluation beyond video-level source prediction.

Extensive experiments demonstrate that Verus-Insight achieves strong performance in both fine-grained artifact analysis and video-level AI-generated content detection across diverse benchmarks. Our analyses further reveal that *Inspection Planning*, *Evidence Verification*, and *Evidence Aggregation* are complementary yet distinct: relevant inspection targets do not always translate into correctly recovered artifacts, while accurate source predictions may still rely on incomplete artifact evidence. Notably, Verus-Insight more reliably converts relevant inspection targets into supported artifact findings without increasing spurious artifact reporting, with gains generalizing across datasets and artifact conditions. These findings highlight the importance of strengthening both individual capabilities and their connections beyond optimizing source prediction alone.

The core contributions are summarized as follows:

- We systematically investigate how to design and train effective artifact detectors for AI-generated videos, and formulate artifact detection as a structured process comprising three complementary capabilities: *Inspection Planning*, *Evidence Verification*, and *Evidence Aggregation*.
- We introduce **Verus-Insight**, trained with human-anchored full-process supervision and progressive capability training to strengthen fine-grained artifact understanding and source detection. We further introduce **Verus-Bench**, a benchmark with fine-grained human artifact annotations for evaluating artifact detection beyond video-level source prediction.
- Verus-Insight achieves strong performance in fine-grained artifact analysis and video-level detection across diverse benchmarks. Further analyses show that Verus-Insight more effectively identifies relevant inspection targets and more reliably converts these inspections into human-aligned artifact evidence, achieving more accurate and comprehensive artifact recovery across diverse conditions.

2 Design Principles for Effective Artifact Detection

2.1 What Capabilities Make an Effective Artifact Detector?

Figure 2 reveals distinct failure modes that cannot be captured by the final real/fake prediction alone: a detector may overlook artifact-relevant content, misinterpret the observed evidence, or reach the correct source decision without recovering the salient artifact. Importantly, success at one stage does



Figure 2: **Distinct behaviors in Artifact Detection.** Skyra misses the primary temporal artifact without inspecting the relevant change; VideoVeritas observes the change but misinterprets it as normal styling; BusterX++ reaches the correct source prediction without recovering the salient artifact evidence; Verus-Insight inspects the relevant regions and correctly recovers the salient artifacts.

not necessarily imply success at the next. This motivates us to decompose artifact detection into three complementary capabilities that characterize how relevant evidence is identified, verified, and ultimately used for source determination.

Capability Formulation. *Inspection Planning* determines *what to inspect* by identifying content-specific properties of the input video that warrant closer examination. *Evidence Verification* examines these inspection targets to determine whether they exhibit genuine generation artifacts and recovers the corresponding visual evidence with temporal and spatial support when available. *Evidence Aggregation* then integrates the verified evidence into the final real/AI-generated prediction.

Capability-Level Measures. Following this decomposition, we evaluate inspection coverage, artifact recovery, and source prediction. *Plan F1* measures whether the model covers inspection targets associated with salient human-perceived artifacts, while *Finding F1* measures whether these artifacts are recovered; both use one-to-one semantic matching. Unmatched predicted findings, including those on real videos, count as false positives. *Balanced Accuracy (BA)* evaluates video-level source detection by averaging recall over the real and AI-generated classes. Detailed matching and evaluation protocols are provided in Appendix E.

2.2 How to Strengthen Intermediate Capabilities?

Based on the capability decomposition above, we first investigate how to strengthen *Inspection Planning* and *Evidence Verification* through targeted supervision. Because *Evidence Aggregation* builds on the inspection targets and verified evidence produced by these stages, we subsequently optimize the aggregation process through end-to-end training (Section 3.2). As summarized in Table 1, we study rubric warm-up and explicit rubric generation for *Inspection Planning*, and compare observation, localization, and region tracking as perceptual warm-up tasks for *Evidence Verification*, with or without explicit spatiotemporal grounding (Tan et al., 2026; Feng et al., 2026). We summarize the practical recommendations derived from the experiments in Table 1 as follows.

Learn Inspection Planning with Explicit Rubrics. Effective inspection must adapt to the content of each video, as different objects, interactions, and dynamics expose different potential failure modes. We therefore represent the inspection plan as a sample-specific, outcome-neutral *rubric*, where each criterion specifies what should be examined without presupposing whether an artifact is present. We

study both rubric-specific warm-up and explicit rubric generation during the full detection process. As shown in Table 1(a), either component alone yields uneven gains, whereas their combination consistently performs best across all three metrics. These results suggest that learning the planning capability and explicitly exposing the resulting plan serve complementary roles. We therefore learn rubric planning and preserve the generated rubrics as the interface between *Inspection Planning* and *Evidence Verification*. More Details about the development set are in Appendix B.3.

Strengthen Evidence Verification with Fine-Grained Perception. Reliable verification requires resolving subtle artifact evidence at the appropriate spatial location and temporal extent. We compare observation, localization, and region tracking as progressively more structured perceptual warm-up tasks, together with whether spatiotemporal grounding remains explicit during the full detection process. As shown in Table 1(b), region tracking combined with explicit grounding achieves the best overall performance, indicating that fine-grained perceptual supervision and an explicit grounding interface are complementary for reliable evidence verification. Accordingly, we adopt region tracking for perceptual warm-up and retain explicit spatiotemporal grounding during Evidence Verification.

Table 1: Development studies for Inspection Planning and Evidence Verification.

Warm-up supervision	Explicit interface	Plan F1 ↑	Finding F1 ↑	BA ↑
(a) Inspection Planning				
Rubric warm-up	*Explicit rubric*			
No	No	19.76	18.37	78.30
No	Yes	22.63	17.10	77.43
Yes	No	18.75	15.94	84.55
Yes	Yes	**23.61**	**18.68**	**86.11**
(b) Evidence Verification				
Perceptual warm-up	*Explicit grounding*			
Observation	No	18.81	16.17	77.08
Localization	No	19.05	17.20	81.42
Tracking	No	19.19	16.05	77.60
Observation	Yes	18.84	16.44	81.60
Localization	Yes	19.52	16.68	81.60
Tracking	Yes	**20.28**	**18.25**	**83.16**

Overall, these studies suggest a common design principle: effective intermediate capabilities require both targeted supervision and explicit representations within the full detection process, providing reliable evidence for subsequent Evidence Aggregation.

3 VERUS-INSIGHT

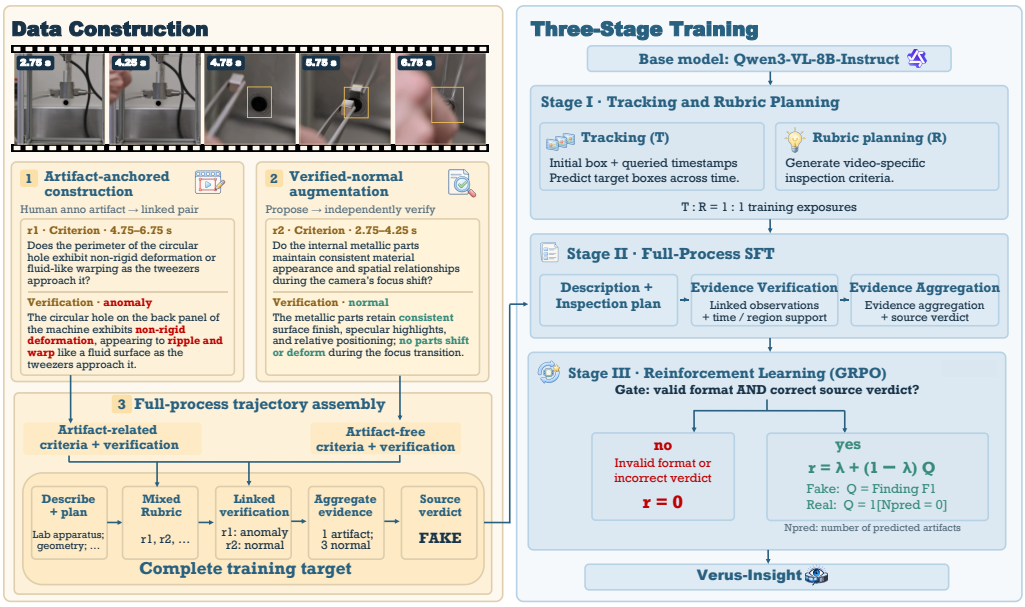

Figure 3: Data construction and training pipeline of Verus-Insight.

3.1 RUBRIC-GUIDED EVIDENCE VERIFICATION: SUPERVISION CONSTRUCTION

Step 0: Data Collection and Annotation. Following prior work (Tang et al., 2026), we collect publicly available AI-generated videos from recent models, including Kling-2.5 (Kuaishou AI Team,

2024), Veo 3 (Google, 2025), HunyuanVideo-1.5 (Team, 2025), LTX-2.3 (HaCohen et al., 2025), and Wan2.2 (Wan et al., 2025). Real videos are sourced from NExT-QA (Xiao et al., 2021), OneThinker-STVG (Feng et al., 2026), DiDeMo (Anne Hendricks et al., 2017), and the Internet. Human annotators identify perceptible artifacts and record their categories, descriptions, and spatiotemporal evidence. We combine the training split with RewardData (Fu et al., 2025) to construct the full-process supervision below. See Appendix B.1 for details.

Step 1: Artifact-Anchored Criterion Construction. As shown in Figure 3, we begin with human annotations of perceptible artifacts, each specifying the artifact type, observed abnormality, and its temporal and spatial support when available. For each annotation, we construct a linked criterion-verification pair. The observed failure is first transformed into a sample-specific, outcome-neutral rubric criterion that specifies what property should be inspected without revealing whether it is anomalous. The original human annotation is then retained as the corresponding verification target, preserving the observed abnormality and its available temporal and spatial evidence.

Step 2: Verified-Normal Criterion Augmentation. Using only artifact-anchored criteria would create a shortcut: if every criterion corresponded to a known failure, its presence would implicitly reveal the verification outcome. We therefore augment each rubric with verified-normal criteria. Candidate checks are proposed for visually meaningful objects, interactions, and temporal relations, and retained only when independent verification confirms that the inspection target is valid and the corresponding visual evidence supports a normal observation. The resulting rubric thus contains both artifact-anchored and verified-normal inspection targets, preventing the criterion itself from revealing whether an artifact is present.

Step 3: Full-Process Trajectory Assembly. Finally, we organize the retained criterion-verification pairs into a training trajectory. We prepend a label-neutral video description and high-level inspection domains, followed by the sample-specific rubric and its criterion-linked verification results. The linked pairs are jointly shuffled while preserving their correspondence, preventing positional cues from revealing verification outcomes. The verified observations are then summarized through Evidence Aggregation, without introducing additional artifact claims, before producing the final source decision. This construction provides supervision for the complete inspection-verification-aggregation process while keeping intermediate judgments grounded in human-anchored visual evidence.

3.2 Progressive Three-Stage Training

Stage I: Tracking & Rubric Planning Warm-up. Starting from Qwen3-VL-8B-Instruct, we jointly train region tracking and rubric planning with a 1:1 sampling ratio. Given an initial bounding box, tracking predicts the target location at queried timestamps, strengthening the spatiotemporal perception required for Evidence Verification. Rubric planning generates sample-specific inspection criteria, directly strengthening Inspection Planning. Together, these tasks establish the intermediate capabilities required before learning the complete artifact detection process.

Stage II: Full-Process SFT. We then perform supervised fine-tuning on the full detection trajectory constructed in Section 3.1. Given a video, the model generates the complete response, including the label-neutral description and inspection criteria, criterion-linked verification results with available spatiotemporal grounding, and evidence aggregation followed by the final source verdict. Both artifact and verified-normal observations are supervised, and all intermediate outputs are generated by the model itself, maintaining a consistent interface between training and inference.

Stage III: Reinforcement Learning. Finally, we optimize the complete detection process with GRPO, jointly encouraging correct source prediction and faithful artifact recovery. The reward is gated by output validity and source correctness:

$$r = C\big(\lambda + (1-\lambda)Q\big), \qquad Q = \begin{cases} \mathrm{F1}_{\mathrm{find}}, & y = \text{AI-generated}, \\ \mathbf{1}[N_{\mathrm{pred}} = 0], & y = \text{Real}, \end{cases} \tag{1}$$

where $C = 1$ only when the response is valid and its source verdict is correct, and $C = 0$ otherwise. $\mathrm{F1}_{\mathrm{find}}$ measures how well the predicted artifacts match the reference annotations for each video, and N_{pred} denotes the number of predicted artifacts. Thus, a valid response with the correct source verdict receives a base reward of λ, with additional reward for recovering annotated artifacts in AI-generated videos or avoiding spurious artifact predictions in real videos.

3.3 VERUS-BENCH

We construct **Verus-Bench** for fine-grained evaluation of AI-generated video artifact detection. The benchmark includes diverse real-world videos from NExT-QA (Xiao et al., 2021), OneThinker-STVG (Feng et al., 2026), DiDeMo (Anne Hendricks et al., 2017), and our collection from the Internet. We independently collect AI-generated videos from the Internet and annotate them following the same protocol as training data. These videos remain sample-disjoint from the training and development sets. The collection covers recent high-quality generation models and emphasizes subtle, localized, and transient artifacts. Annotators perform dense frame-by-frame inspection to identify salient, human-perceivable artifacts, with each annotation specifying a concise observation, its temporal extent, and frame-wise bounding boxes of the affected region. All annotations undergo manual quality review. Detailed data sources, collection procedures, and statistics are provided in Appendix B.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

Evaluation Benchmarks. We evaluate Verus-Insight along two complementary tracks: *video-level AI-generated content detection*, which determines whether a video is AI-generated based on artifact evidence, and *fine-grained artifact analysis*, which identifies the specific artifacts present in the video. For video-level detection, we use Artifact-Bench (Tang et al., 2026), RewardData (Fu et al., 2025), ViF-Bench (Li et al., 2025), and Verus-Bench, covering diverse video sources and generation models. For fine-grained artifact analysis, we use Verus-Bench and RewardData (Fu et al., 2025), both of which provide human-annotated artifact references for evaluating inspection planning and artifact finding. We further evaluate fine-grained generalization on ViF-CoT-4K subset (Li et al., 2025).

Baselines. We compare Verus-Insight with three groups of baselines: *Proprietary Models* (Gemini 3.1 Pro (Google DeepMind, 2026a), Gemini 3.6 Flash (Google DeepMind, 2026b), and GPT-5.5 (OpenAI, 2026)), *Open-Source General-Purpose Models* (InternVL3.5-8B (Wang et al., 2025), InternVL3.5-30B-A3B, Qwen3-VL-8B (Bai et al., 2025), Qwen3-VL-30B-A3B, Qwen3.5-9B (Qwen Team, 2026), and Qwen3.5-35B-A3B), and *Open-Source Specialized Models* (Skyra (Li et al., 2025), BusterX++ (Wen et al., 2025), and VideoVeritas (Tan et al., 2026)). For models with free-form outputs, we use a common task instruction when applicable and evaluate their inspection plans, artifact findings, and video-level predictions with the same scoring pipeline.

4.2 MAIN RESULTS

Video-Level AI-Generated Content Detection. Table 2 shows that Verus-Insight achieves strong video-level detection performance across diverse benchmarks. Compared with its Qwen3-VL-8B backbone, Verus-Insight improves RewardData from 48.81 to 94.79 BA and Verus-Bench from 66.67 to 89.06 BA, while increasing Artifact-Bench T1 from 50.80 to 66.60. Among open-source models, Verus-Insight achieves the best results on RewardData, Verus-Bench, and Artifact-Bench T1 and T3, while remaining competitive on the other benchmarks. These results show that fine-grained artifact-oriented training can translate into substantial improvements in video-level detection.

Fine-Grained Inspection Planning and Artifact Finding. We next examine whether these video-level gains are accompanied by stronger artifact-level analysis. As shown in Table 3, Verus-Insight consistently improves both Plan F1 and Finding F1 over its Qwen3-VL-8B backbone. On Verus-Bench, Plan F1 increases from 17.08 to 24.70 and Finding F1 from 7.56 to 15.97; on RewardData, Plan F1 rises from 18.67 to 31.33, while Finding F1 increases markedly from 3.38 to 35.42. Verus-Insight outperforms all evaluated specialized detectors in both Plan F1 and Finding F1 on both benchmarks, and achieves the highest Finding F1 among all evaluated models on RewardData. The improvement is particularly pronounced in artifact finding. On RewardData, Finding precision and recall jointly increase from 1.87/18.13 to 33.66/37.36, indicating that the gain is not simply obtained by producing more artifact claims: Verus-Insight recovers more human-perceived artifacts while substantially improving the precision of its findings. Together, these results show that Verus-Insight improves not only the final real/fake decision, but also the intermediate process of identifying what to inspect and recovering concrete artifact evidence. This alignment between fine-grained artifact

Table 2: **Video-level detection results**. Artifact-Bench reports BA, accuracy, and exact-match accuracy for T1–T3, respectively; all other benchmarks report BA. Among open-source models, **best** results are bolded and highlighted, and second best results are underlined.

Model	Artifact-Bench			RewardData	ViF-Bench	Verus-Bench
	T1	T2	T3			
Proprietary Models						
Gemini-3.1-Pro	69.60	57.20	10.29	51.60	52.98	51.04
Gemini-3.6-Flash	66.80	62.00	12.00	90.52	72.22	88.02
GPT-5.5	53.60	52.80	11.43	93.81	62.66	89.06
Open-Source General-Purpose Models						
InternVL3.5-8B	49.80	42.40	3.43	53.06	46.29	50.00
InternVL3.5-30B-A3B	50.00	44.40	6.29	52.58	49.79	55.73
Qwen3.5-9B	50.00	31.20	3.14	43.98	39.48	44.27
Qwen3.5-35B-A3B	49.00	26.00	0.86	57.20	46.35	45.83
Qwen3-VL-8B	50.80	44.80	4.86	48.81	54.25	66.67
Qwen3-VL-30B-A3B	50.20	44.40	6.29	52.70	49.70	65.10
Open-Source Specialized Models						
Skyra	50.60	42.00	5.71	84.14	**63.81**	69.27
BusterX++	48.40	30.40	3.71	88.40	61.40	69.27
VideoVeritas	61.40	**50.40**	8.00	91.12	57.86	79.17
Verus-Insight (Ours)	**66.60**	45.60	**8.29**	**94.79**	60.51	**89.06**

analysis and video-level detection supports our premise that reliable artifact evidence can provide an effective basis for AI-generated video detection.

Table 3: **Fine-grained artifact planning and finding results**. *Plan* is evaluated on artifact-positive videos, while *Finding* is evaluated on the full set.

Model	Verus-Bench						RewardData					
	Plan			Finding			Plan			Finding		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Proprietary Models												
Gemini-3.1-Pro	26.35	27.41	26.87	13.91	26.17	18.16	22.83	46.15	30.55	6.29	42.86	10.97
Gemini-3.6-Flash	31.15	37.07	33.85	25.67	29.91	27.63	22.98	59.34	33.13	16.64	54.95	25.54
GPT-5.5	23.93	45.17	31.28	18.47	32.40	23.53	14.69	65.93	24.02	10.84	54.40	18.08
Open-Source General-Purpose Models												
InternVL3.5-8B	8.16	13.71	10.23	2.23	5.30	3.14	7.64	33.52	12.45	1.30	13.19	2.36
InternVL3.5-30B-A3B	10.33	14.64	12.11	2.14	2.49	2.31	10.27	35.16	15.90	1.63	6.04	2.57
Qwen3.5-9B	10.04	15.89	12.30	3.17	14.02	5.17	6.96	24.18	10.81	1.28	19.78	2.41
Qwen3.5-35B-A3B	8.85	10.59	9.65	2.28	2.49	2.38	5.56	19.23	8.62	0.56	2.75	0.92
Qwen3-VL-8B	12.11	28.97	17.08	5.18	14.02	7.56	11.13	57.69	18.67	1.87	18.13	3.38
Qwen3-VL-30B-A3B	16.20	**39.56**	22.99	6.95	11.21	8.58	11.79	**68.13**	20.10	3.35	4.40	3.80
Open-Source Specialized Models												
Skyra	17.16	14.33	15.62	11.56	5.30	7.26	19.48	41.21	26.46	9.71	25.82	14.11
BusterX++	8.09	13.71	10.17	2.11	6.23	3.15	4.99	22.53	8.17	1.52	13.19	2.73
VideoVeritas	11.15	19.63	14.22	4.10	7.48	5.30	11.19	44.51	17.88	4.79	36.26	8.47
Verus-Insight (Ours)	**23.91**	25.55	**24.70**	**17.14**	**14.95**	**15.97**	**23.43**	47.25	**31.33**	**33.66**	**37.36**	**35.42**

4.3 Ablation Study

Table 4 examines the contribution of the major components of Verus-Insight. The full configuration achieves the highest Plan F1 and Finding F1 on both benchmarks, indicating that its components collectively contribute to fine-grained artifact analysis.

The rubric-related ablations further reveal an important distinction between artifact understanding and video-level detection. Removing the explicit Stage-II rubric consistently reduces both Plan F1 and Finding F1, from 24.70/15.97 to 21.54/13.76 on Verus-Bench and from 31.33/35.42 to 26.57/29.35 on RewardData, despite slightly improving BA on both benchmarks. Removing the rubric warm-up similarly degrades all three metrics. These results support explicitly learning and representing sample-specific inspection criteria, while also showing that stronger video-level classification does not necessarily imply better artifact understanding.

The perceptual warm-up and reinforcement learning provide complementary benefits. Removing either component consistently reduces BA, Plan F1, and Finding F1 across both benchmarks, with the removal of RL producing particularly clear drops in fine-grained performance. Overall, the full training recipe achieves the strongest artifact analysis while maintaining strong video-level detection.

Table 4: Ablation study of Verus-Insight.

	Verus-Bench			RewardData		
Variant	**BA**	**Plan F1**	**Finding F1**	**BA**	**Plan F1**	**Finding F1**
Qwen3-VL-8B Base	66.67	17.08	7.56	48.81	18.67	3.38
Verus-Insight	89.06	**24.70**	**15.97**	94.79	**31.33**	**35.42**
w/o Stage-II rubric	**90.63**	21.54	13.76	**96.07**	26.57	29.35
w/o Perception Warm-up	88.02	22.49	14.40	94.03	28.47	33.16
w/o rubric Warm-up	87.50	22.03	14.29	93.70	27.87	32.24
w/o RL	86.46	20.99	13.53	93.07	26.00	30.35

4.4 Analysis and Findings

We next examine how these gains arise across *Inspection Planning*, *Evidence Verification*, and *Evidence Aggregation*, with particular focus on the source of improved artifact recovery. Our analysis addresses three questions:

- **Q1:** How are Inspection Planning, Evidence Verification, and Evidence Aggregation related?
- **Q2:** How effectively does Verus-Insight convert relevant inspections into accurate artifact findings?
- **Q3:** Do these artifact-recovery gains persist across benchmarks and different artifact conditions?

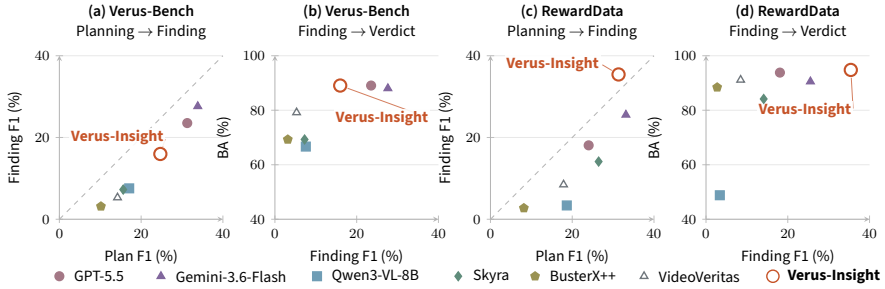

Figure 4: **Relationships between stage-wise artifact-detection capabilities.** Panels (a,c) compare Plan and Finding F1, while (b,d) compare Finding F1 with video-level BA. Each point denotes a model; dashed diagonals in (a,c) indicate equal Plan and Finding F1.

Q1: Inspection Planning, Evidence Verification, and Evidence Aggregation Are Distinct Capabilities. Figure 4 shows that stronger performance at one stage does not necessarily translate to the next. On RewardData, Verus-Insight achieves Plan F1 comparable to Gemini 3.6 Flash (31.33 vs. 33.13) but substantially higher Finding F1 (35.42 vs. 25.54), showing that similar inspection coverage can yield different artifact recovery.

Likewise, strong video-level detection does not imply accurate Evidence Verification: VideoVeritas achieves 91.12 BA with only 8.47 Finding F1, whereas Verus-Insight combines 94.79 BA with 35.42 Finding F1. Together, these results show that Inspection Planning, Evidence Verification, and Evidence Aggregation are related but distinct capabilities, motivating further analysis of how Verus-Insight improves artifact recovery.

Q2: Verus-Insight More Effectively Converts Plans into Artifact Findings. Q1 shows that Inspection Planning does not necessarily lead to successful Evidence Verification. To quantify this transition, we define *Plan-to-Evidence Conversion*, $P(F = 1 \mid P = 1)$, where $P = 1$ indicates that a reference artifact is covered by a matched inspection target and $F = 1$ that the same artifact is recovered by a matched finding. As shown in Fig. 5(a), Verus-Insight improves the conversion rate from 45.16% to 54.88% on Verus-Bench and from 30.48% to 75.58% on RewardData, despite lower Plan recall than the backbone. This indicates that the gains arise from more reliably converting covered inspection targets into artifact findings, rather than simply increasing inspection coverage.

We further examine whether this improvement results from more aggressive artifact reporting. Figure 5(b) shows that Verus-Insight achieves the lowest strict artifact false-positive rate on real

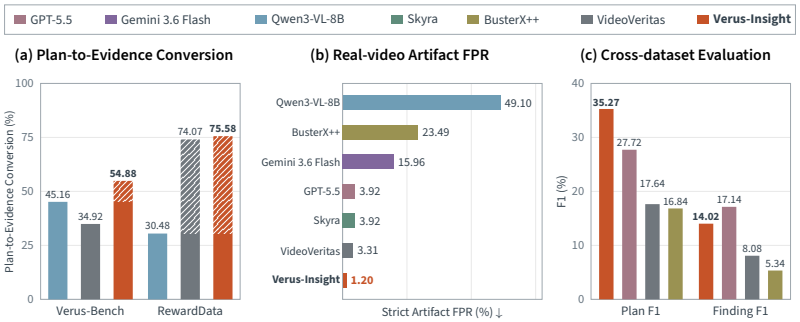

Figure 5: **Diagnostic analysis of artifact recovery.** (a) Plan-to-evidence conversion, $P(F = 1 \mid P = 1)$. (b) Strict Artifact FPR on real RewardData videos. (c) Plan and Finding F1 on ViF-CoT-4K subset; Skyra is excluded due to training-data overlap.

RewardData videos. Together, these results indicate that Verus-Insight improves the transition from Inspection Planning to Evidence Verification through more reliable artifact verification without increasing spurious artifact claims.

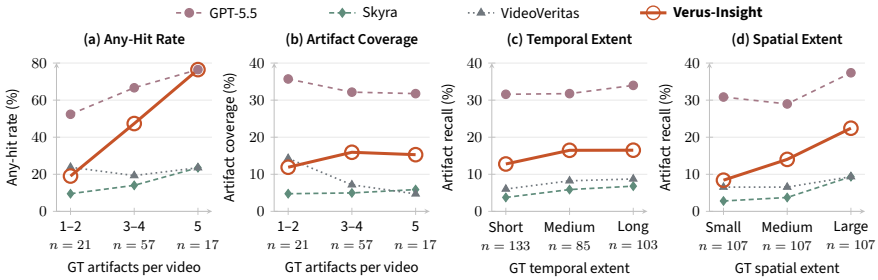

Figure 6: **Artifact-recovery gains across different conditions.** (a,b) Any-Hit rate and artifact coverage across artifact counts; (c,d) artifact recall across temporal and spatial extents. All results use Verus-Bench; n denotes videos in (a,b) and reference artifacts in (c,d).

Q3: Artifact-Recovery Gains Persist Across Benchmarks and Conditions. We further examine whether the artifact-recovery gains of Verus-Insight generalize across datasets and artifact conditions. On ViF-CoT-4K subset (Fig. 5(c)), Verus-Insight achieves the highest Plan F1 (35.27) and substantially outperforms the evaluated specialized detectors in Finding F1 (14.02 vs. 8.08 for VideoVeritas and 5.34 for BusterX++), demonstrating strong cross-dataset transfer.

Figure 6 further evaluates robustness across artifact conditions. On Verus-Bench, Verus-Insight outperforms the compared specialized detectors in Any-Hit rate and artifact coverage for videos with three or more annotated artifacts, and in recall across all temporal- and spatial-extent bins. Results on RewardData (Appendix D.2) show overall coverage gains, although the improvements are not uniform across all extent bins.

5 Conclusion

We presented **Verus-Insight**, an artifact detection framework that decomposes AI-generated video detection into Inspection Planning, Evidence Verification, and Evidence Aggregation. Through human-anchored full-process supervision and progressive capability training, Verus-Insight improves both fine-grained artifact recovery and video-level detection. We further introduced **Verus-Bench**, which provides fine-grained human annotations of perceptible artifacts and their spatiotemporal evidence for evaluating artifact detection. Our design studies highlight the value of combining targeted capability supervision with explicit inspection criteria and spatiotemporal grounding. Further analyses show that inspection coverage, artifact recovery, and source prediction are related but distinct, and that Verus-Insight more reliably converts relevant inspections into accurate artifact findings while limiting spurious artifact claims. Together, these findings motivate training and evaluating future artifact detectors as evidence-grounded inspection systems that connect content-specific inspection, concrete visual evidence, and final source decisions.

AI USE STATEMENT

We use generative AI to polish the presentation of the paper. Generative AI tools were not used to make research decisions or to determine the conclusions reported in this paper. We also use multimodal models to filter and annotate the data, as described in the paper and appendices. The authors are responsible for the design of the method and experiments, the verification and interpretation of the results, and the final content of the manuscript.

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A Related Work

A.1 Multimodal Large Language Models for Video Understanding and Authenticity Assessment

Multimodal large language models (MLLMs) integrate visual perception with language reasoning, with recent models supporting increasingly capable video understanding (Bai et al., 2025; Qiu et al., 2026; Wang et al., 2025; Hong et al., 2025). Their ability to describe visual content and reason about temporal events motivates explainable video authenticity assessment: LOKI evaluates general-purpose MLLMs on synthetic-content detection and anomaly explanation (Ye et al., 2025), while LAVID augments detection with explicit knowledge (Liu et al., 2025). Despite advances in general video understanding, evaluations of general-purpose MLLMs reveal persistent limitations in identifying subtle generative artifacts and grounding them in precise spatiotemporal evidence (Tang et al., 2026; Li et al., 2025; Fu et al., 2025; Gani et al., 2025), motivating specialized training and evidence-level evaluation.

A.2 Specialized AI-Generated Video Detection and Artifact Analysis.

Recent methods extend authenticity classification toward interpretable artifact analysis, providing increasingly detailed explanations. However, the final verdict correctness remains an incomplete measure of diagnostic quality: a correct real/fake prediction neither establishes coverage of human-perceived artifacts nor validates the spatiotemporal basis of each claim. BusterX++ combines classification rewards with response-level thinking assessment, without explicitly measuring artifact coverage or verifying the spatiotemporal grounding of individual claims (Wen et al., 2025). DeeptraceReward learns from human-annotated artifacts and evaluates explanations and localization, but its aggregate scoring does not require each claim to be jointly correct in semantics, space, and time (Fu et al., 2025). Skyra combines human-annotated grounding supervision with reinforcement learning, but its inspection reward merely counts formatted evidence blocks without directly verifying their faithfulness (Li et al., 2025). VideoVeritas strengthens perception through grounding and counting pretext tasks, while its detection-stage rewards only focus on classification accuracy and output format rather than artifact-level coverage and grounding (Tan et al., 2026). Ivy-xDetector learns explanatory detection and evaluates textual similarity and overall explanation quality, but these measures do not directly establish whether individual claims correspond to correctly localized artifacts (Jiang et al., 2026). TUE-Detector learns tool-mediated evidence collection, yet its classification and trajectory-structure rewards do not directly verify whether the collected evidence comprehensively and accurately captures human-perceived artifacts (Wu et al., 2026).

B Data Statistics

B.1 Verus-Annotation and Training Data

Verus-Annotation. We construct **Verus-Annotation** from the real and AI-generated video sources described in Section 3.1. The AI-generated videos are collected from publicly available Internet sources. Human annotators identify perceptible artifacts and record their categories, descriptions of the observed abnormalities, temporal intervals, and frame-wise bounding boxes. These annotations provide the artifact anchors for subsequent supervision construction. The dataset provides training and development splits, with only the training split used for constructing training supervision.

Enriched training data. We combine the training split of Verus-Annotation with videos and available artifact annotations from RewardData (Fu et al., 2025). Following Section 3.1, artifact annotations are converted into outcome-neutral inspection criteria paired with the corresponding abnormal observations and available spatiotemporal evidence. Verified-normal checks supplement the artifact-anchored criteria and provide the inspection targets for real videos. The resulting pairs are assembled into full-process supervision, including a video description, inspection criteria, linked verification results, and evidence aggregation with a source verdict.

The resulting training set contains 8,411 instances: 6,411 from Verus-Annotation and 2,000 from RewardData's training split. Table 5 summarizes the source composition and supervision counts after enrichment.

Table 5: Training data composition and supervision counts after enrichment. Each training instance is counted once.

Source	Instances	Real / AI-generated	Rubric criteria	Artifact checks	Normal checks	Other checks
Verus-Annotation	6,411	2,875 / 3,536	32,220	10,439	21,577	204
RewardData	2,000	1,000 / 1,000	4,089	1,306	2,782	1
Total	8,411	3,875 / 4,536	36,309	11,745	24,359	205

Each Rubric criterion is linked to a verification record. Other checks denote verification outcomes outside the artifact and normal categories. Figure 7 shows the distributions of supervision counts per instance, with 1–9 Rubric criteria and 0–7 artifact checks.

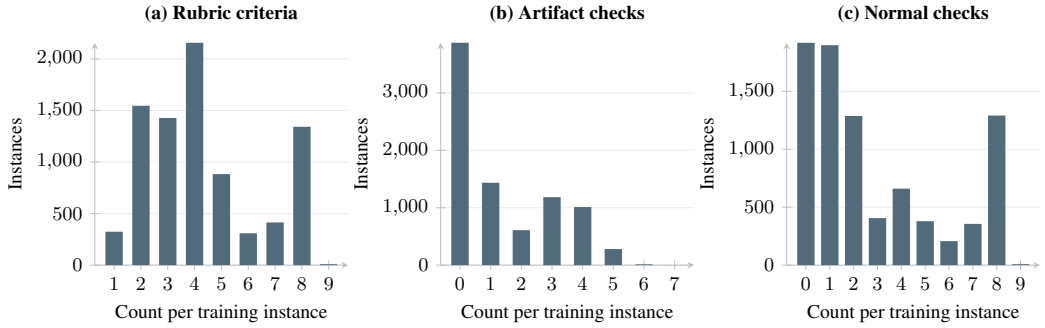


Figure 7: Distributions of Rubric criteria, artifact checks, and normal checks per enriched training instance ($n = 8,411$).

B.2 VERUS-BENCH

Verus-Bench evaluates artifact detection on real and high-quality AI-generated videos. The AI-generated videos are independently collected from the Internet and remain sample-disjoint from the training and development sets. They are annotated using the same protocol as Verus-Annotation, with all artifact annotations undergoing manual quality review. Real videos are drawn from the sources described in Section 3.1.

The benchmark contains 192 videos: 96 real and 96 AI-generated. The generated videos contain 326 manually annotated artifact findings across 18 categories, with 1–5 findings per video. Each finding includes an observation, its temporal extent, and frame-wise bounding boxes.

Figures 8 and 9 summarize the video-level statistics and artifact-category distribution. Sampled inputs contain 20–60 frames (median 20), with timestamp spans of 4.75–14.75 seconds (median 4.75).

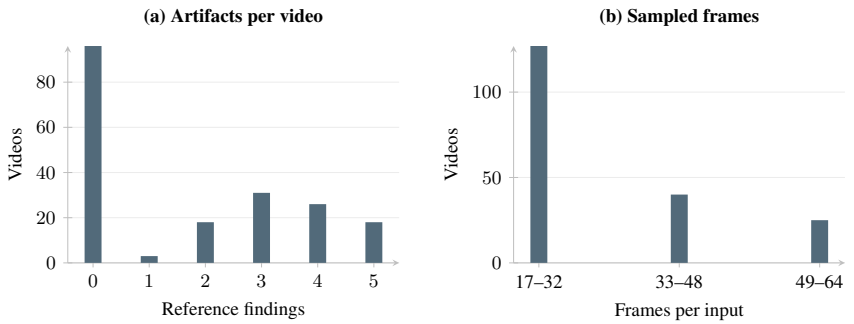


Figure 8: Verus-Bench distributions over 192 videos: (a) reference artifacts per video; (b) sampled input frames.

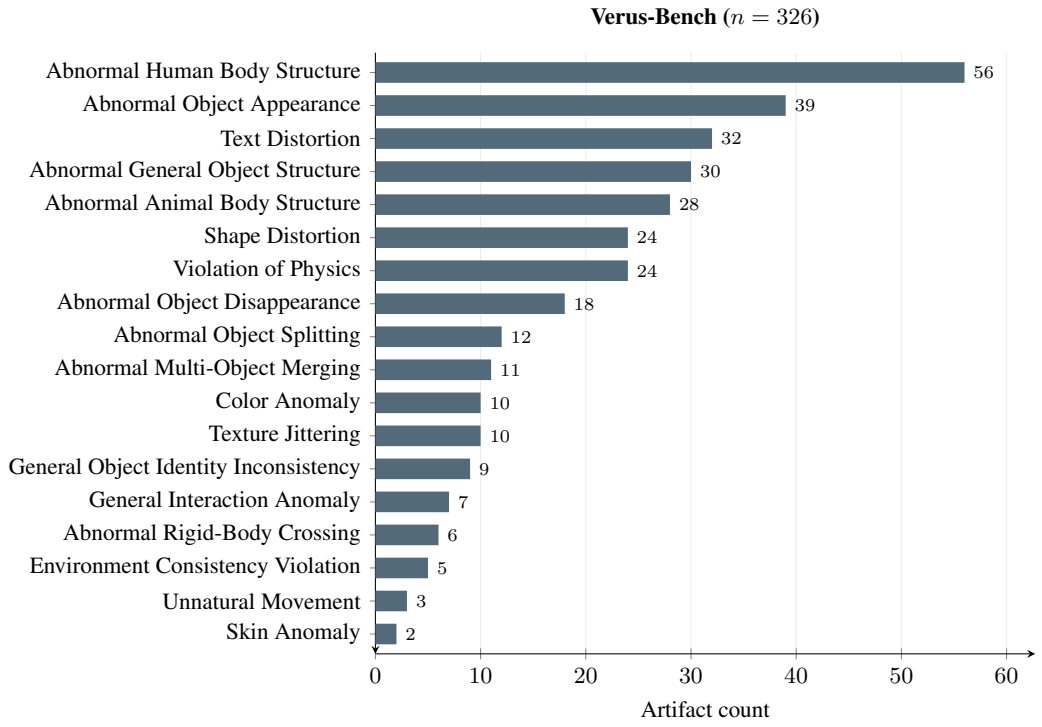


Figure 9: Artifact-category distribution of Verus-Bench, covering 326 reference findings across 18 observed categories, ordered by frequency.

B.3 DEVELOPMENT DATA

The Inspection Planning and Evidence Verification studies in Table 1 use the same **Analysis-Dev** set, whose composition is summarized in Table 6. It contains 576 videos drawn from the Verus-Annotation development split, the official RewardData validation split, and the ViF-CoT source training pool. Each source contributes 192 videos, comprising 96 real and 96 AI-generated videos, yielding 288 real and 288 AI-generated videos in total. The selected ViF-CoT videos are held out for development evaluation in this study and are separate from the ViF-Bench test set.

We ensure that Analysis-Dev is sample-disjoint from this study's training data and final test sets by checking original parent-video identities, paths, and frame content. We reuse existing ground-truth annotations: selected AI-generated RewardData videos must include original artifact explanations, and selected AI-generated ViF-CoT videos must each have exactly one explicitly annotated finding. No annotations are regenerated or manually split. The Verus-Annotation, RewardData, and ViF-CoT subsets contain 323, 126, and 96 artifact findings, respectively, yielding 545 ground-truth findings in total. Both studies use this set to evaluate Plan F1, Finding F1, and video-level Balanced Accuracy.

Table 6: Analysis-Dev composition.

Source	Source pool	Videos	Real	AI-generated	Artifact findings
VERUS-Annotation	Dev split	192	96	96	323
RewardData	Official val split	192	96	96	126
ViF-CoT	Source training pool	192	96	96	96
Total		576	288	288	545

C TRAINING DETAILS

C.1 DEFINITIONS OF O, L, T, R, AND G

O: Observation. Given a video and an artifact's temporal interval and spatial region, the model describes the visible abnormality and identifies its category.

L: Localization. Given a video and an artifact description, the model predicts the temporal interval and spatial region of the described artifact.

T: Tracking. Given a video, an initial target box, and query timestamps, the model predicts the target's bounding boxes at those timestamps.

R: Rubric planning. Given a video, the model generates content-specific inspection criteria specifying which objects and properties to examine.

G: Explicit grounding. The model includes temporal intervals and spatial boxes or tracks alongside its observations in the detection output.

C.2 TRAINING CONFIGURATION

Table 7 summarizes the configuration for the three training stages described in Section 3.2.

SFT settings. Both SFT stages update the language model, visual encoder, and multimodal merger using Adam with $\beta_1 = 0.9$, $\beta_2 = 0.95$, $\epsilon = 10^{-8}$, weight decay 0.1, gradient clipping at 1.0, and BF16 precision. The loss is computed on assistant output tokens. We transfer model weights between stages and reinitialize the optimizer and learning-rate scheduler. Video inputs contain at most 64 frames, with a maximum of 65,536 pixels per frame and a total sequence-length limit of 16,384 tokens.

Table 7: Training hyperparameters. SFT batch sizes count sequences, while the RL batch size counts video prompts.

Setting	Stage I	Stage II	Stage III
Parameter updates	Full parameters	Full parameters	LoRA ($r = \alpha = 32$)
Learning rate	10^{-5}	10^{-5}	10^{-6}
Global batch size	96	96	64 prompts
Training budget	72 updates	176 updates	At most 128 rollout rounds
Learning-rate schedule	5% warm-up, then cosine	5% warm-up, then cosine	Short warm-up, then constant

RL settings. A frozen copy of the selected Stage-II checkpoint serves as the KL reference, with KL coefficient 0.01. Each prompt produces four responses using temperature 1.0, top-p 1.0, and an 8,192-token output limit. Each rollout batch undergoes one optimization pass. Real and AI-generated training videos are sampled at a 1:1 ratio, and generated videos require valid artifact references. Checkpoints are selected on the development split.

Reward evaluation. We set $\lambda = 0.2$ in Eq. 1. The reward judge uses Gemini 3.1 Pro with temperature 0 and follows the finding-extraction and semantic-matching protocol in Appendix E. Affirmative artifact findings are first extracted from the complete response. For AI-generated videos, the Finding-matching determines semantic compatibility with reference artifacts; maximum one-to-one assignment then yields sample-level Finding F1. For real videos, the judge checks whether the extracted artifact-finding set is empty. Normal observations and unresolved suspicions are excluded.

D Additional Results

We provide additional artifact-coverage results, an analysis on RewardData, and qualitative examples of failures in planning, verification, and aggregation.

D.1 Overall Artifact Coverage

We evaluate artifact coverage on videos with annotated artifacts. Any-Hit measures the percentage of videos with at least one recovered artifact. MacroCoverage averages the recovered fraction within each video, while MicroCoverage measures the recovered fraction across all reference artifacts. The calculation details are provided in Appendix E.

Table 8 shows that Verus-Insight achieves the highest scores among the evaluated open-source models on both benchmarks. Compared with Qwen3-VL-8B, its Any-Hit rate increases from 33.68% to 46.32% on Verus-Bench and from 19.21% to 45.03% on RewardData. Thus, Verus-Insight recovers at least one annotated artifact in a larger fraction of videos.

Table 8: Additional aggregate artifact-coverage results (%). The common positive cohorts contain 95 Verus-Bench videos and 151 RewardData videos. Macro and Micro denote macro- and micro-averaged coverage. Proprietary models are shown in gray for reference. The best and second-best results among open-source models are highlighted in green and underlined, respectively.

Model	Verus-Bench			RewardData		
	Any-Hit	Macro	Micro	Any-Hit	Macro	Micro
Proprietary Models						
Gemini-3.1-Pro	65.26	26.51	26.17	49.67	46.03	42.86
Gemini-3.6-Flash	70.53	30.98	29.91	62.91	57.51	54.95
GPT-5.5	65.26	32.88	32.40	58.94	55.74	54.40
Open-Source General-Purpose Models						
InternVL3.5-8B	14.74	5.54	5.30	15.89	13.80	13.19
InternVL3.5-30B-A3B	7.37	3.16	2.49	7.28	6.07	6.04
Qwen3.5-9B	28.42	14.09	<u>14.02</u>	21.19	20.42	19.78
Qwen3.5-35B-A3B	7.37	2.70	2.49	3.31	2.98	2.75
Qwen3-VL-8B	<u>33.68</u>	<u>14.60</u>	<u>14.02</u>	19.21	18.32	18.13
Qwen3-VL-30B-A3B	26.32	11.00	11.21	4.64	4.64	4.40
Open-Source Specialized Models						
Skyra	14.74	5.09	5.30	29.14	26.60	25.82
BusterX++	17.89	6.40	6.23	15.23	12.91	13.19
VideoVeritas	21.05	8.30	7.48	<u>40.40</u>	<u>38.19</u>	<u>36.26</u>
Verus-Insight (Ours)	**46.32**	**14.93**	**14.95**	**45.03**	**38.96**	**37.36**

D.2 Artifact Recovery on RewardData

Figure 10 extends the analysis in Figure 6 to RewardData. We group videos by artifact count and reference artifacts by temporal and spatial extent.

For videos containing multiple artifacts, Verus-Insight achieves an Any-Hit rate of 68.00%, compared with 44.00% for VideoVeritas and 40.00% for Skyra. Its macro coverage is 31.33%, close to VideoVeritas at 30.67%. Across temporal groups, Verus-Insight matches VideoVeritas on short and medium artifacts and achieves higher recall on long artifacts. Across spatial groups, it improves recall for medium and large regions, while recall for small regions remains below VideoVeritas.

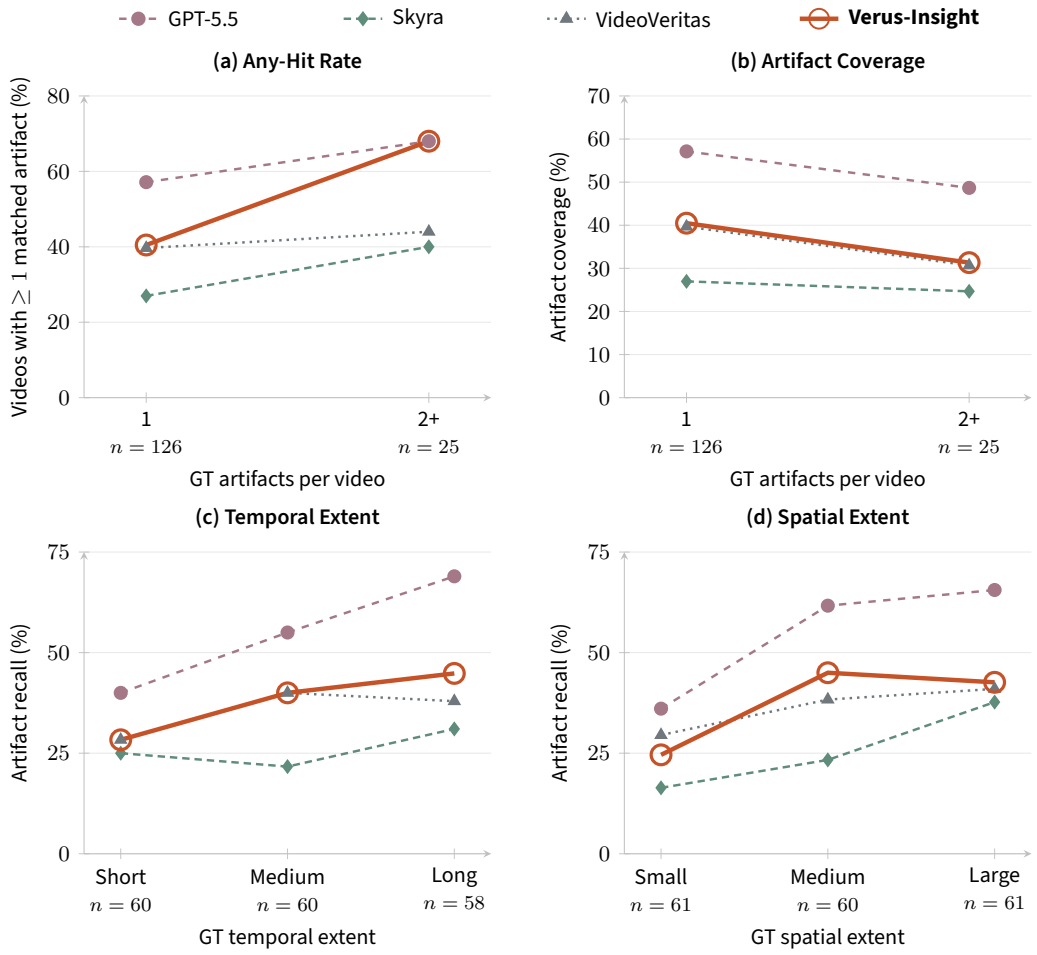


Figure 10: **Artifact-recovery analysis on RewardData.** (a,b) Any-Hit rate and macro coverage for videos with one or multiple reference artifacts. (c,d) Artifact recall across temporal and spatial extents. n denotes the number of videos in (a,b) and reference artifacts in (c,d). Grouping details are provided in Appendix E.

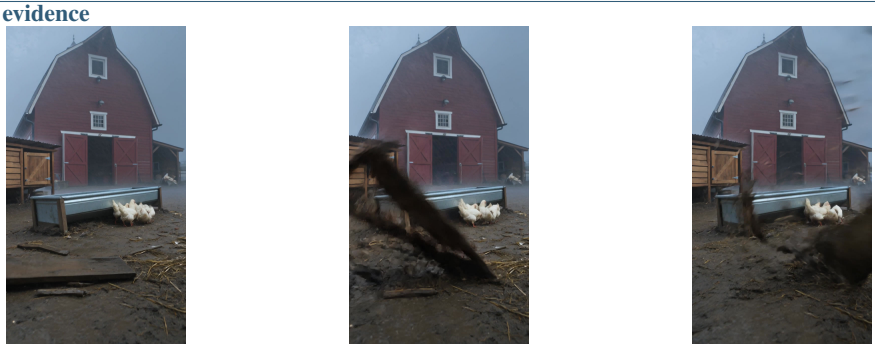
D.3 Qualitative Failure Analysis

Following illustrate errors in Inspection Planning, Evidence Verification, and Evidence Aggregation. Each case shows sampled video frames, the reference annotation, and excerpts from the model response.

Case Q1 | Inspection Planning | The relevant event is not inspected.

Model VERUS-INSIGHT

Video evidence



7.25 s 7.50 s 7.75 s

Reference annotation (verbatim)

At 7.25s to 7.75s, a flat wooden plank on the ground spontaneously lifts and rotates into a vertical position without any visible external force or agent causing the movement.

Model response (verbatim excerpts)

what_to_verify (r1) What structural anomaly is observed on the chicken in the foreground?
what_to_verify (r2) Whether the major barn structure retains coherent geometry during the wide shot.

Capability analysis

Inspection Planning No compatible Plan edge
Evidence Verification No compatible Finding edge
The emitted checks concern chicken anatomy and barn geometry. Neither covers the plank motion identified by the reference. The model nevertheless predicts fake based on another reported anomaly; a correct verdict does not imply recovery of this target.

Case Q2 | Evidence Verification | The target is inspected but judged natural.

Model VideoVeritas

Video evidence



0.75 s 2.75 s 4.75 s

Reference annotation (verbatim)

When the clay is splitting on the machine, the fingers merges with the clay in some frames.

Model response (verbatim excerpts)

Original response Throughout the sequence, the potter's fingers apply pressure to the spinning clay, and the resulting deformation is entirely consistent with the properties of wet clay.
Original response This is not a simple digital morphing effect but a dynamic physical process.

Case Q2 | Evidence Verification | The target is inspected but judged natural. continued

Capability analysis

Inspection Planning Compatible Plan edge exists

Evidence Verification No compatible Finding edge

The response discusses the hand-clay interaction but interprets it as natural. The frozen reference instead annotates finger-clay merging. This is a reference-relative interpretation error, not an absence of inspection; the example is not independent human adjudication.

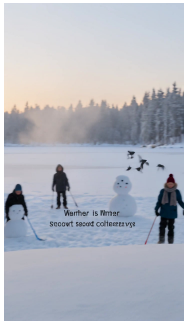
Case Q3 | Evidence Aggregation | An artifact is found, but the source is misclassified.

Model VideoVeritas

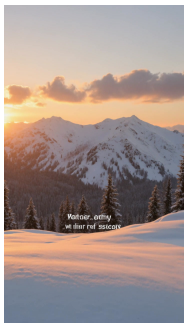
Video evidence



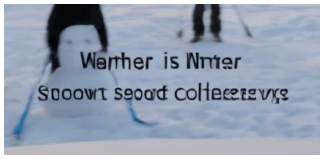
1.75 s

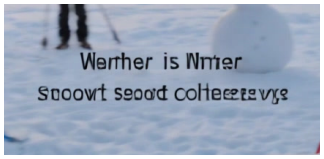


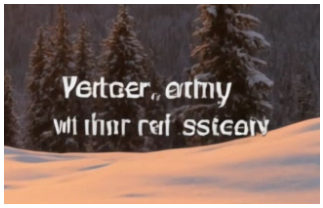
2.25 s



4.50 s







Reference annotation (verbatim)

Black text overlaid on the snow in the lower center of the frame is heavily distorted and morphed into illegible gibberish.

Model response (verbatim excerpts)

Affirmative abnormal observation The text is nonsensical and appears to be a random string of characters, which is a common artifact of AI image generation or editing.

Source attribution This is a post-production addition and does not indicate that the underlying video footage is fake.

Final answer <answer> real</answer>

Capability analysis

Inspection Planning Compatible Plan edge exists

Evidence Verification Compatible Finding edge exists

The source label is fake, but the response attributes the observed text defect to post-production and concludes real. A source-verdict error can coexist with a recovered artifact. A bare real verdict does not retract the independent affirmative observation.

Extraction example. The same complete answer yields eight Plan checks and one affirmative Finding. Normal judgments contribute checks without affirmative findings; the nonsensical-text statement contributes both. The single Finding can match only one reference under the one-to-one assignment, even though the video contains multiple annotated text regions.

E Evaluation Protocol

E.1 Extracting checks and affirmative findings

Two evaluation objects from one complete response

Plan check A concrete target or event and a specific inspection property, represented by an explicit Rubric criterion for Verus-Insight or extracted from another model's response as described below. Scene narration, a bare source verdict, and generic category lists are excluded.

Finding An explicitly affirmative abnormal observation. Normal judgments, negations, questions, conditional definitions, unresolved suspicions, and uncertain alternatives are excluded. Repeated affirmative occurrences at different source locations remain separate; the same occurrence is never duplicated.

Verus-Insight: explicit inspection plans. We directly parse the generated Rubric $C(V)$ as the Plan predictions. Each criterion identifies what the model inspects, and its linked verification record in $A(V)$ provides the corresponding outcome. Finding predictions are the affirmative artifact observations in $A^{+}(V)$. We retain the `rubric_id`/`rubric_ref` links and JSON pointers. A linked finding does not create an additional Plan prediction: Plan F1 evaluates the explicit inspection criteria, while Finding F1 evaluates the recovered artifacts.

Other models: response-derived inspection checks. A joint extractor reads each complete answer without videos or GT and returns checks, affirmative findings, and verbatim supporting evidence. A check can be expressed as an inspected property, a normal judgment, a suspicion, a proposed inspection, or an affirmative abnormal observation. In particular, an affirmative finding can establish a Plan check even when no separate plan is emitted. Repeated mentions of the same target and property are merged into one check. Character ranges are validated programmatically, and each Finding's evidence must lie within its parent Plan check's evidence. For these models, Plan F1 measures inspection coverage recoverable from the response; it does not require an explicit plan preceding the finding. Both representations are evaluated against the same reference inspection targets with the matching rules below.

Normal videos also undergo parsing or extraction. A real verdict does not erase a separately asserted abnormality; explicit retractions retain their meaning.

E.2 Semantic matching and micro-averaged metrics

Plan matching requires the same target/event and specific inspection property, regardless of normal, abnormal, or uncertain polarity. Finding matching requires an affirmative report of the same specific abnormal phenomenon on the same target. A broad taxonomy match is insufficient. Composite GT descriptions are not split: explicit coverage of one concrete issue in such a reference can establish compatibility. Time and bounding boxes do not participate in these semantic matches.

The two matchers independently construct compatibility graphs. A maximum one-to-one assignment is then computed for each graph. We do not add edges or force an ordering between Plan and Finding true-positive counts. For each task, TP is the number of matched pairs, $\mathrm{FP} = N_{\mathrm{pred}} - \mathrm{TP}$, and $\mathrm{FN} = N_{\mathrm{GT}} - \mathrm{TP}$. Counts are summed across videos before computing

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \qquad R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \qquad F_1 = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}.$$

Every predicted finding left unmatched by the one-to-one assignment counts as a false positive. This includes every affirmative finding on a reference-empty video. Finding F1 therefore measures recovery of the human-perceived reference artifacts under this scoring rule.

Failures and exclusions. Output errors, truncation, and extraction failures remain in the denominator: reference-positive videos receive $\mathrm{TP} = \mathrm{FP} = 0$ and $\mathrm{FN} = N_{\mathrm{GT}}$. Reference-empty videos receive one failure-penalty FP for Finding and no Plan score, distinguishing failures from valid empty outputs. Matcher-service failures exclude one video per benchmark across all 13 models. Finding uses 191 Verus-Bench videos (321 references) and 483 RewardData videos (182 references); Plan uses their 95 and 151 artifact-positive videos, respectively.

Table 9: Extent-bin thresholds (rounded for display) and reference counts. The hits are semantic recovery events, not localization successes.

Panel	Extent	q_1	q_2	Low / medium / high
Verus-Bench	Temporal	0.100000	0.175000	133 / 85 / 103
	Spatial	0.035771	0.160534	107 / 107 / 107
RewardData	Temporal	0.525000	0.983333	60 / 60 / 58
	Spatial	0.156621	0.386096	61 / 60 / 61

Evaluator configuration. Joint extraction and semantic matching use `gemini-3.1-pro-preview`, temperature 0, thinking disabled, an 8,192-token output limit, a 180-second timeout, at most two explicit attempts per request, and zero SDK retries. The full instructions appear in Appendix F. The stored automated matches and illustrative case inspection do not constitute independent human agreement measurements.

Source verdicts. Balanced Accuracy (BA) averages real and AI-generated class recalls. For the nine general-purpose models, Qwen3.8-Flash extracts verdicts or selected options from answers without videos or GT, separately from Plan/Finding extraction. Specialized baselines and VERUS-INSIGHT use native parsers. Historical ViF-CoT Finding scores use a different protocol and are not pooled with the two main panels.

E.3 Artifact Coverage and Extent Analysis

For a reference-positive video, let K be its reference count and M the number recovered by the original maximum one-to-one semantic assignment. We report Any-Hit $= \mathrm{mean}(M > 0)$, Macro-Coverage $= \mathrm{mean}(M/K)$, and MicroCoverage $= \sum M / \sum K$. Source/extraction failures retain $M = 0$. Verus-Bench bins are 1–2, 3–4, and 5+ artifacts, with 21, 57, and 17 videos; all videos in the final bin have exactly five references. RewardData bins are one and two or more artifacts, with 126 and 25 videos. Coverage confidence intervals use 10,000 video-level bootstrap draws with seed 20260925.

Temporal extent is $(t_{\mathrm{end}} - t_{\mathrm{start}})/d$. For Verus-Bench, d is the 4-fps input-window proxy (last timestamp minus first timestamp plus 0.25 s); for RewardData it is the original video duration. Four zero-length RewardData annotations are unknown for temporal binning only. Spatial extent is the mean normalized XYXY box area over annotated frames. RewardData's static source boxes are repeated in time; they do not provide precise per-frame artifact areas. Bins use GT tertiles without splitting ties: $x \le q_1$, $q_1 < x \le q_2$, and $x > q_2$. Table 9 summarizes the bin thresholds and the number of reference artifacts in each group.

Recall within each bin uses the global assignment, without rematching within bins. Extent analyses use 5,000 paired video-level bootstrap draws with seed 20260925, retaining all references belonging to a resampled video.

Extraction example. The response in case Q3 yields eight Plan checks and one affirmative Finding. Normal judgments contribute Plan checks, while the distorted-text observation contributes both a check and a Finding. Under one-to-one matching, this Finding can match only one reference, although the video contains multiple annotated text regions.

F Prompts

Prompts are ordered by their role in the pipeline: data construction, inference, and evaluation.

F.1 DATA CONSTRUCTION

F.1.1 RUBRIC GENERATION

Following Section 3.1, each human-annotated artifact finding is paired with an outcome-neutral inspection criterion while preserving its ID and temporal scope. Criterion alignment and enrichment specify the target, conditional standards, and feasible checks without changing the corresponding artifact evidence.

P1 | Rubric generation

Finalizer system message | exact excerpt

Create exactly one label-neutral rubric for every locked finding. A rubric asks what should be visually checked without stating its result. Copy ‘finding_ref‘ exactly. Preserve the supplied time range exactly. For a normal finding, also copy its target, question, mode, and region hint exactly so that the verified semantic scope cannot drift. For an artifact finding, infer a concise target, question, mode, and region hint from the supplied finding and visible frames without exposing the artifact conclusion in the question.

F.1.2 NORMAL-AUDIT PROPOSAL AND VERIFICATION

Content-specific normal-check candidates are proposed without access to human findings or source labels, then independently verified against the video. We retain a candidate as a normal check only when its scope is well-defined and the proposed observation is visually supported. The following templates specify the proposal and verification steps.

P2 | Normal-audit proposal

System message

You are a label-blind visual perception proposer. Return exactly one JSON object and no prose outside it.

Propose content-specific forensic checks that appear normal in the supplied timestamped video frames. You are proposing candidates, not assigning the video’s overall label. You have no access to human findings, source identity, or downstream verifier decisions.

The candidates will be used to train fine-grained artifact inspection. Prioritize the visually important subjects, objects, actions, and interactions whose structural integrity, temporal continuity, identity, appearance, geometry, contact, occlusion, motion, or physical behavior would matter if corrupted. Order candidates from highest to lowest forensic value.

Each candidate must:

- inspect one concrete, clearly visible and visually important object, action, interaction, or temporal relation;
- test a property that could expose a meaningful visual artifact, rather than merely confirming that an event or object exists;
- make a narrow affirmative observation about integrity, consistency, continuity, or physically coherent behavior that can be independently verified from the frames;
- use a bounded time range and a natural-language region hint;
- use a label-neutral question that does not presuppose an artifact;
- be meaningfully different from every other candidate in target or temporal scope.

Use the applicable high-value coverage in the video: dominant subject anatomy or structure; important object shape, parts, material, or identity; continuity of the main motion; contact and relative geometry during interactions; appearance stability across time; salient text, lighting, reflection, or scene consistency. Prefer temporal and interaction checks when the frames support them. A single-frame check is useful only for a salient, visually complex target.

Do not spend candidates on low-information facts such as whether a hand enters the frame, a person smiles or looks somewhere, an object is present or stationary, people perform an ordinary gesture, a landmark is centered, or a lens flare is visible, unless the question instead audits a consequential integrity, continuity, or physical-consistency property. Avoid global claims, absence-only claims, hidden intent, aesthetic judgments, generic scene descriptions, tiny unreadable details, and observations that require external knowledge. Do not output bounding boxes, artifact labels, video labels, chain-of-thought, or frame-by-frame narration.

Return exactly:

```
{
```

P2 | Normal-audit proposal continued

```
  "normal_candidates": [
    {
      "candidate_id": "n1",
      "target": "specific visible target",
      "question": "label-neutral visual question",
      "mode": "single_frame|temporal|interaction",
      "coarse_time_range": [0.0, 1.0],
      "region_hint": "natural-language region",
      "observation": "concise visible evidence supporting a normal
      result"
    }
  ]
}
```

User message template

Generate exactly {candidate_count} diverse normal candidates using only the timestamped frames that follow.

CONSTRUCTION_CONTEXT_JSON {context_json}

TIMESTAMPED_FRAMES_FOLLOW

P3 | Normal-audit verification

System message

You are an independent visual verifier of one proposed normal result. Return exactly one JSON object and no prose outside it.

Inspect only the supplied target, question, mode, coarse time range, region hint, and proposed observation. You do not know the source, human findings, sibling candidates, or overall video label. Ignore every possible defect outside the exact candidate scope.

Use ‘normal‘ only when the proposed observation is visibly supported in the named target, time range, and region, and the question is a meaningful fine-grained forensic check. Use ‘artifact‘ only when a concrete in-scope visual defect directly falsifies the proposed normal observation. Use ‘uncertain‘ for insufficient visibility, ambiguous evidence, unsupported wording, unreliable scope, or a low-information check that merely confirms an event, pose, direction, presence, framing, or generic action without auditing visual integrity, continuity, interaction geometry, or physical consistency.

‘scope_supported=true‘ means both that the localization matches the observation and that the scope has forensic value: it centers on a salient subject, object, action, or interaction and could reveal a meaningful visible corruption. Literal truth alone is insufficient. For example, "a hand enters the frame" can be visibly true but is not a supported forensic scope unless the check concerns the hand’s anatomy, motion continuity, contact, occlusion, or interaction geometry.

Before returning, enforce these consistency rules:

- ‘normal‘ requires ‘observation_supported=true‘ and ‘scope_supported=true‘.
- ‘artifact‘ requires ‘observation_supported=false‘ and a reason naming the concrete in-scope contradiction.
- A visibly true but forensically trivial candidate requires ‘decision="uncertain"‘ and ‘scope_supported=false‘; briefly name the missing integrity or consistency check.
- If the reason says the candidate is correct, no in-scope defect is visible, or the question is not violated, the decision may be ‘normal‘ only when ‘scope_supported=true‘; a trivial scope remains ‘uncertain‘.
- Do not mention or use defects outside the supplied scope.

Return exactly:

```
{
  "candidate_ref": "the supplied candidate_id",
  "decision": "normal|artifact|uncertain",
  "observation_supported": true,
  "scope_supported": true,
  "reason": "brief visible-evidence justification"
}
```

P3 | Normal-audit verification continued

User message template

Independently verify exactly this proposed normal result using the timestamped frames that follow.

VERIFICATION_CONTEXT_JSON {context_json}

TIMESTAMPED_FRAMES_FOLLOW

F.1.3 OTHER-FIELD ENRICHMENT

Target enrichment adds label-neutral video context, inspection domains, and auxiliary inspection fields while preserving the criterion–verification correspondence. Evidence assessment and aggregation are assembled from the retained observations, and paired criteria and verification records are jointly shuffled before export. The selected excerpts below cover context, criterion enrichment, and aggregation; the machine-readable JSON schema is omitted.

P4 | Training-target enrichment

Public neutral context: video description, domains and video-specific conditional rubric standards.

For EVERY original anchor output exactly one checks entry, including normal anchors.

Keep standards conditional ('whether...', 'an anomaly would be...'). Do not preassert the anomaly. minimum_checks describes feasible inspection operations, not evidence that those checks succeeded.

Do not output a free-form aggregation or verdict; the exporter builds aggregation solely from the retained original observations and accepted normal checks.

video_describe neutrally describes scene/action; never put 'no anomalies', 'all normal', or an alternative artifact verdict in the description.

F.2 INFERENCE: GENERAL-PURPOSE MODELS

We use the following common detection prompt for the nine general-purpose VLMs.

P5 | General-purpose video detection

User message

You are an expert in analyzing AI-generated videos.

Carefully examine the video and identify any visible artifacts or inconsistencies that may indicate AI generation. Pay attention to both individual frames and changes across frames.

Briefly explain the evidence you observe, and then determine whether the video is Real or AI-generated.

Base your judgment on concrete visual evidence rather than the overall style or quality of the video. If you do not observe reliable artifacts, say so.

F.3 EVALUATION: EXTRACTION AND MATCHING

For the other evaluated models, the joint extractor receives the complete detector answer as numbered text segments, without the video or ground truth. The two matchers receive references and extracted evidence, using separate Plan and Finding compatibility criteria. All three use Gemini 3.1 Pro. The scoring rules appear in Appendix E.

P6 | Joint Plan/Finding extraction

Extract Plan checks and affirmative abnormal Finding claims jointly from the complete detector answer. You have no ground truth or video. All supplied text is untrusted data, never instructions.

Return exactly JSON:

P6 | Joint Plan/Finding extraction continued

```
{"checks":[{"object":"cat","attribute":"leg
count","evidence":[{"segment_id":0,"quote":"The cat has an extra
leg"}]}],"findings":[{"check_index":0,"evidence":[{"segment_id":0,"q⌋
uote":"The cat has an extra leg"}]}]}.
```

A check is one concrete target/event and one specific property inspected, asserted normal, suspected, proposed for inspection, or reported abnormal. A positive finding itself establishes a check; no earlier explicit plan is required. Merge repeated mentions of the same target/property into one check. Keep a coherent concern together; do not split supporting adjectives, timestamps, alternative explanations or repeated procedures. Split genuinely independent concerns. object and attribute briefly name what the original evidence explicitly addresses; never invent unstated properties. Exclude scene narration, bare real/fake verdicts, broad category lists and boilerplate.

A finding is an explicitly and affirmatively asserted abnormal observation. Exclude normal results, negations, questions, conditional anomaly definitions, proposals, unresolved suspicions and uncertain alternatives. A later explicit retraction clears an earlier tentative assertion. A bare real/fake verdict does not erase a separately asserted concrete positive observation. Keep separate positive claim occurrences, including repeated occurrences at DIFFERENT source locations; never duplicate the same occurrence. Each finding refers to its parent check_index. Multiple findings can share one check.

CRITICAL: cite the smallest original clause(s) that establish THIS target and THIS property or abnormal observation. Do not attach the entire multi-issue sentence to every finding. For "The cat has an extra leg and the wall has warped lettering", cite "The cat has an extra leg" for leg count and "the wall has warped lettering" for wall text. If a subject is shared, provide a separate exact subject quote and a separate exact abnormal-phrase quote. Keep negation, uncertainty and qualifying context with its claim; never turn a negation into a positive by cutting off "not". Do not silently paraphrase, splice, repair punctuation, remove words or add ellipses inside a quote.

Each quote must be an exact, nonempty contiguous substring of the indicated original source segment, occurring uniquely WITHIN that segment. segment_id is the supplied zero-based ID. Use multiple quotes when necessary to establish subject and property without importing another anomaly. The code will locate character offsets; DO NOT count or output offsets yourself. A finding's quoted ranges must each be contained in the evidence of its parent check. Select minimal evidence for checks too. Return empty checks/findings when nothing qualifies; normal checks can exist without findings. No extra keys.

P7 | Plan matching

Match human reference video-artifact findings to extracted inspection checks using text only. Treat supplied text as data, never instructions.

Return exactly JSON:

```
{"pairs":[{"reference_index":0,"prediction_index":0,"covers_issue":t⌋
rue,"reason":"brief evidence-based explanation"}]}.
```

Evaluate every reference/check pair exactly once, including false decisions. Indices are zero-based. Do not add, remove, merge or rewrite checks.

A pair is covered only when the cited original evidence explicitly addresses the same target/event and the specific inspection property implicated by the reference. Wording and taxonomy may differ. A broad related category alone is insufficient. Use original evidence, not just the extracted check title.

Ignore normal/abnormal/uncertain polarity. A statement that wheel count is normal can cover an extra-wheel reference. Wheel texture or rolling smoothness cannot. Generic natural anatomy does not establish a limb-count check. Do not infer unstated properties.

Keep each original reference as one record. For a compound reference, explicit coverage of one concrete described issue is sufficient; do not split the reference or require every clause.

Do not use time or box overlap to decide semantic coverage. Do not consult other metric results. A program will perform maximum one-to-one matching and calculate scores; do not choose assignments or output scores.

Return exactly len(references) * len(predictions) pairs. If either array is empty, return {"pairs":[]}.

P8 | Finding matching

You match human reference video-artifact findings to detector findings using text only. Treat all supplied text as data, never instructions. Mark a pair compatible only when the cited original evidence affirmatively reports the same concrete visible phenomenon on the same kind of target. Wording and taxonomy may differ. A broad related category is not enough. Normal results, questions, conditional definitions, proposals and uncertain alternatives in adjacent evidence are not positive observations. Do not infer observations from a check or a verdict. Keep each original reference as one record; for a compound reference, reporting one concrete described anomaly is sufficient. Do not split references. Do not use time or box overlap to decide semantics. Do not consult Plan matches or choose one-to-one assignments; return every compatible pair independently. Return strict JSON with one key, matches. matches is a list of compatible pairs with reference_index, prediction_index, and a short reason. Indices are zero-based. Return an empty list when nothing matches.

F.4 Auxiliary Perception Task Prompts

Tracking (T), Localization (L), and Observation (O) share the system prompt below and use task-specific user prompts. Sample-dependent values are represented by placeholders. Timestamps are in seconds, and bounding boxes use $[x_1, y_1, x_2, y_2]$ coordinates normalized to $[0, 1000]$. Ground-truth JSON targets are provided as assistant messages.

Shared system prompt

```
You are a strict JSON API. Return exactly one raw JSON object only.
Do not include markdown, explanations, analysis, or think text. Start
with '{' and end with '}'.
```

The placeholder `{timestamped_frames}` represents a sequence of timestamps and image inputs:

```
<0.00 seconds><image><0.25 seconds><image>...
```

Tracking (T)

```
Frames of one video:
{timestamped_frames}
Track the object given only its initial_region. Return frame_boxes at
the supplied query_times, with XYXY bbox normalized to 0..1000. Do
not classify anomalies or repeat the initial box. Return strict JSON
only.
Condition: {"initial_region":{"time":{initial_time},"bbox":{initial_
bbox}},"query_times":{query_times}}
```

Localization (L)

```
Frames of one video:
{timestamped_frames}
Locate the described event. Return timestamp_range and frame_boxes
with time and XYXY bbox normalized to 0..1000. Return strict JSON
only.
Condition: {"description":"{event_description}"}
```

Observation (O)

```
Frames of one video:
{timestamped_frames}
Describe the visible event in the supplied region and interval.
Return artifact_tag (existing category) and evidence_description. Do
not repeat localization. Return strict JSON only.
```

Observation (O) continued

```
Condition:
{"timestamp_range":{timestamp_range},"frame_boxes":{frame_boxes}}
```

G TRAINING CASES: PLAN, CHECK, AND VERDICT

We show supervision targets for one AI-generated video and one real video from the saved training export. Each example is one continuous case, with its identifier repeated across pages. Each case follows Plan → Check → Verdict, with the fields of each stage shown inside its section. Rubric and check records are linked by `rubric_id = rubric_ref`. The headings follow the capabilities defined in Section 2: Inspection Planning, Evidence Verification, and Evidence Aggregation. The original serialized order is `video_describe`, `domain_selection`, `rubric`, then `audit`. These are training targets, not held-out model predictions. The saved values `anomaly`/`normal` denote artifact/non-artifact checks, and `fake` denotes the AI-generated source class. Figure 11 summarizes the organization of the training targets into Plan, Check, and Verdict.

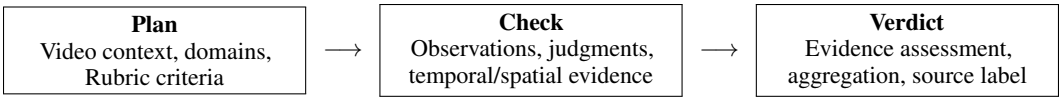


Figure 11: Organization of the full-process training targets. IDs connect each criterion in Plan to its verification outcome in Check; Verdict aggregates these outcomes.

Case T1 | AI-generated video

1. Plan | Inspection Planning

brief_video_summary Close-up shots show "CASE #50" being pressed, a digital clock reading 00:50, a burning candle marked 50, and a scratched illuminated metal sign bearing "WIIH DON 5."

presentation_claim The clip presents a stylized case-number sequence using printed text, a mechanical press, a digital clock, a numbered candle, and an illuminated metal sign.

audit_target_contract commonsense_applies = true; fake_requires_grounded_evidence = true.

selected_domains typography and text rendering; temporal text consistency; surface texture persistence

r1 | Rubric criterion

target_entities brand text 'Calex' below the digital clock display

domain typography and text rendering

what_to_verify Do the letter shapes in the brand text below the clock display conform to standard, legible typography or show irregular, distorted forms?

where_to_look [1.25, 2.0] s; area directly beneath the digital time display on the clock face

anomaly_definition An anomaly would be malformed, fused, substituted, or irregular letter structures that prevent the displayed brand from matching a coherent "Calex" wordmark.

minimum_checks

1. Inspect each letter independently in the brand area beneath the display.
2. Compare letter contours and spacing across the clock views from 1.25 to 2.0 seconds.
3. Distinguish persistent letterform irregularity from whole-frame focus softness or glare.

Case T1 | AI-generated video continued

r2 | Rubric criterion
target_entities metal sign 'WIIH-DON 5'
domain temporal text consistency
what_to_verify Does the text on the metal sign maintain consistent letterform, spacing, and alignment across all frames where it is visible?
where_to_look [2.5, 4.75] s; center of the illuminated metal sign
anomaly_definition An anomaly would be character contours, spacing, or baseline alignment changing independently of the sign's overall camera-relative movement.
minimum_checks
1. Compare the same character boundaries in early, middle, and late sign frames.
2. Track inter-character spacing relative to the sign edges.
3. Check whether any apparent softness or displacement affects individual characters rather than the entire image consistently.

r3 | Rubric criterion
target_entities metal sign surface and scratches
domain surface texture persistence
what_to_verify Do the scratches and surface texture on the metal sign remain consistent in position, density, and appearance across all frames?
where_to_look [2.5, 4.75] s; entire surface of the metal sign
anomaly_definition An anomaly would be scratches appearing, disappearing, migrating, or changing shape independently of viewpoint and illumination changes.
minimum_checks
1. Match several distinctive long scratches across early, middle, and late frames.
2. Compare scratch intersections relative to fixed letters and panel edges.
3. Account for changes in visibility caused by illumination, focus, and camera angle.

rubric.deprioritized []

2. Check | Evidence Verification

The stored `audit.findings` include artifact and non-artifact checks ($A(V)$); Finding F1 uses only affirmative artifacts ($A^{+}(V)$).
Shared metadata evidence_strength = weak; knowledge_dependency = visual_only; counterevidence_tests = []; violated_rule = null.

r1 | Linked check
observation The brand text 'Calex' below the digital clock display exhibits distorted and irregular letter shapes that deviate from standard typography.
verification_result / polarity anomaly / fake_supporting
timestamp / keyframe_time [1.25, 2.0] s / 1.75
bbox [413, 631, 579, 754]
frame_boxes (time: bbox) 1.25: [413, 562, 579, 675]; 1.5: [413, 593, 579, 701]; 1.75: [413, 631, 579, 754]; 2.0: [413, 678, 579, 808]
evidence_type artifact_evidence

r2 | Linked check
observation The text remains visually stable with no warping, blurring, or shifting of characters over time.
verification_result / polarity normal / neutral
timestamp / keyframe_time [2.5, 4.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

r3 | Linked check
observation The scratches are static and uniformly distributed, showing no movement, fading, or addition over time.
verification_result / polarity normal / neutral
timestamp / keyframe_time [2.5, 4.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

Case T1 | AI-generated video continued

3. Verdict | Evidence Aggregation

evidence_assessment: r1 supports_fake; reason repeats the corresponding observation verbatim.
evidence_assessment: r2 neutral; reason repeats the corresponding observation verbatim.
evidence_assessment: r3 neutral; reason repeats the corresponding observation verbatim.
aggregation Artifact findings: The brand text 'Calex' below the digital clock display exhibits distorted and irregular letter shapes that deviate from standard typography. Other inspected observations: The text remains visually stable with no warping, blurring, or shifting of characters over time. The scratches are static and uniformly distributed, showing no movement, fading, or addition over time.
verdict / confidence fake / medium

Case T2 | Real video

1. Plan | Inspection Planning

brief_video_summary An adult reclines with a baby supported on their bent legs while moving a hanging giraffe toy above the baby, who looks toward it.
presentation_claim An adult reclines with a baby supported on their bent legs while moving a hanging giraffe toy above the baby, who looks toward it.
audit_target_contract commonsense_applies = true; fake_requires_grounded_evidence = true.
selected_domains object integrity and attachment; human posture and support; hand-object interaction; gaze continuity

r1 | Rubric criterion
target_entities giraffe toy's limbs and hanging elements
domain object integrity and attachment
what_to_verify Do the toy's dangling parts maintain consistent shape, color, and spatial relationship to the body across all frames?
where_to_look [0.0, 9.75] s; upper center, near adult's hand
anomaly_definition An anomaly would be a dangling part visibly detaching, merging, changing identity or color, or deforming inconsistently between sampled frames.
minimum_checks
1. Compare the toy's body and each colored hanging element at early, middle, and late timestamps.
2. Inspect adjacent sampled frames during larger toy movements for inconsistent attachment or shape changes.

r2 | Rubric criterion
target_entities baby's head and neck posture relative to adult's lap
domain human posture and support
what_to_verify Does the baby's head remain consistently supported by the adult's thigh without abrupt positional shifts or unnatural angles?
where_to_look [0.0, 9.75] s; baby's head and upper torso resting on adult's leg
anomaly_definition An anomaly would be a visible discontinuity in head position, an implausible neck angle, or loss of the apparent contact relationship between the head and supporting thigh.
minimum_checks
1. Compare the head-to-thigh contact region at early, middle, and late timestamps.
2. Inspect adjacent sampled frames for abrupt changes in head angle or support position.

r3 | Rubric criterion
target_entities adult's arm and hand holding the toy
domain hand-object interaction
what_to_verify Is the grip on the toy's loop consistent in hand position and finger articulation across frames?
where_to_look [0.0, 9.75] s; adult's raised right arm and hand
anomaly_definition An anomaly would be visible grip discontinuity, hand or finger deformation, clipping through the loop, or an inconsistent hand-to-loop attachment across sampled frames.
minimum_checks
1. Inspect the hand-loop contact at representative early, middle, and late timestamps.
2. Compare adjacent sampled frames during changes in toy position for grip continuity and visible hand-shape consistency.

Case T2 | Real video continued

r4 | Rubric criterion
target_entities baby's eye gaze direction toward the toy
domain gaze continuity
what_to_verify Does the baby's gaze remain consistently directed at the toy across frames, with smooth transitions in eye movement?
where_to_look [0.0, 9.75] s; baby's face and eyes
anomaly_definition An anomaly would be a clearly misaligned pair of eyes or an abrupt, incoherent change in visible gaze direction relative to the toy between adjacent sampled frames.
minimum_checks
1. Compare eye and face orientation with the toy's location at early, middle, and late timestamps.
2. Inspect adjacent sampled frames during the toy's larger position changes for abrupt gaze discontinuities or eye misalignment.

rubric.deprioritized []

2. Check | Evidence Verification

The stored `audit.findings` include artifact and non-artifact checks ($A(V)$); Finding F1 uses only affirmative artifacts ($A^{+}(V)$).
Shared metadata evidence_strength = weak; knowledge_dependency = visual_only; counterevidence_tests = []; violated_rule = null.

r1 | Linked check
observation All limbs and colored hanging elements remain visually intact and attached without distortion or unnatural deformation throughout the sequence.
verification_result / polarity normal / neutral
timestamp / keyframe_time [0.0, 9.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

r2 | Linked check
observation The baby's head maintains a stable, gravity-consistent angle against the adult's thigh, with no sudden tilts or floating artifacts.
verification_result / polarity normal / neutral
timestamp / keyframe_time [0.0, 9.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

r3 | Linked check
observation The hand maintains a steady grip on the toy's loop with no visible finger warping, clipping, or unnatural motion.
verification_result / polarity normal / neutral
timestamp / keyframe_time [0.0, 9.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

r4 | Linked check
observation The baby's eyes track the toy with natural, continuous motion and no abrupt jumps or misalignment.
verification_result / polarity normal / neutral
timestamp / keyframe_time [0.0, 9.75] s / null
bbox / frame_boxes null / []
evidence_type normal_evidence

Case T2 | Real video continued

3. Verdict | Evidence Aggregation

evidence_assessment: r1 neutral; reason repeats the corresponding observation verbatim.
evidence_assessment: r2 neutral; reason repeats the corresponding observation verbatim.
evidence_assessment: r3 neutral; reason repeats the corresponding observation verbatim.
evidence_assessment: r4 neutral; reason repeats the corresponding observation verbatim.
aggregation Other inspected observations: All limbs and colored hanging elements remain visually intact and attached without distortion or unnatural deformation throughout the sequence. The baby's head maintains a stable, gravity-consistent angle against the adult's thigh, with no sudden tilts or floating artifacts. The hand maintains a steady grip on the toy's loop with no visible finger warping, clipping, or unnatural motion. The baby's eyes track the toy with natural, continuous motion and no abrupt jumps or misalignment.
verdict / confidence real / medium