

# BusterX: MLLM-Powered AI-Generated Video Forgery Detection and Explanation

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Project Page: <https://github.com/18cv/BusterX>

## Abstract

*Advances in AI generative models facilitate super-realistic video synthesis, amplifying misinformation risks via social media and eroding trust in digital content. Several research works have explored new deepfake detection methods on AI-generated images to alleviate these risks. However, with the fast development of video generation models, such as Sora and WanX, there is currently a lack of large-scale, high-quality AI-generated video datasets for forgery detection. In addition, existing detection approaches predominantly treat the task as binary classification, lacking explainability in model decision-making and failing to provide actionable insights or guidance for the public. To address these challenges, we propose GenBuster-200K, a large-scale AI-generated video dataset featuring 200K high-resolution video clips, diverse latest generative techniques, and real-world scenes. We further introduce BusterX, a novel AI-generated video detection and explanation framework leveraging multimodal large language model (MLLM) and reinforcement learning for authenticity determination and explainable rationale. To our knowledge, GenBuster-200K is the first large-scale, high-quality AI-generated video dataset that incorporates the latest generative techniques for real-world scenarios. BusterX is the first framework to integrate MLLM with reinforcement learning for explainable AI-generated video detection. Extensive comparisons with state-of-the-art methods and ablation studies validate the effectiveness and generalizability of BusterX. The code, models, and datasets will be released.*

## 1. Introduction

Recent advances in generative AI [14, 47, 58] have revolutionized the synthesis of photorealistic images and videos, achieving fidelity that challenges human perceptual discrimination. While these innovations empower creative and industrial applications, they simultaneously introduce unprecedented risks of malicious exploitation. This dual-use dilemma has catalyzed urgent efforts to develop robust forgery content detection methods, particularly for high-quality AI-generated video content.

To mitigate these risks, researchers have prioritized AI-generated content (AIGC) detection as a specific research area. The rapid improvement in AIGC quality has made it difficult to distinguish between synthetic and authentic media, highlighting the need for AI-driven detection systems that provide interpretable explanations for decision-making. Significant strides [22, 61] have been made in AI-generated image detection using Multimodal Large Language Model (MLLM) to assess authenticity and explain their decisions. However, video forgery detection lags behind, as existing synthetic videos are easily identifiable, thereby reducing the demand for an advanced MLLM-based detection and explanation framework. With generative techniques, such as Sora [39] and WanX [53], now producing highly realistic videos, the need for comprehensive, high-quality video datasets and interpretable, robust detection frameworks has become urgent.

Although there are several datasets [6, 10, 24, 25, 35, 37] for video forgery detection, they exhibit the following limitations: **1) Constrained Authenticity.** Current benchmarks [10, 24, 25] predominantly employ outdated video generation techniques, producing relatively low-fidelity synthetic content that is easy to detect by both humans and mod-

els. **2) Limited Forensic Scope.** Existing datasets [25, 43] focus narrowly on isolated manipulation types, leaving them vulnerable to adversarial attacks and unable to generalize to emerging synthesis paradigms. For instance, classic Deepfake datasets like FF++ [43] and Celeb-DF [25] primarily concentrate on face-swap techniques. **3) Bias and Fairness Deficits.** Existing datasets [6, 10, 24, 25, 35, 37] often exhibit insufficient demographic diversity and contextual variety, causing detection models to develop biased accuracy patterns across ethnicities, genders, and environmental conditions, which undermines both fairness and real-world reliability.

To address these limitations, we propose **GenBuster-200K**, a rigorously curated dataset of 200,000+ high-quality video clips engineered as a comprehensive benchmark for video forgery detection. Table 1 provides a systematic comparison highlighting GenBuster-200K’s advantages over existing datasets across multiple perspectives. GenBuster-200K stands out for its use of state-of-the-art (SOTA) generation methods, high frame rate, superior resolution, and extensive scene diversity. Notably, it excels at producing realistic and temporally consistent videos. To the best of our knowledge, GenBuster-200K is the first large-scale, high-quality dataset specifically designed for real-world forensic scenarios, setting a new benchmark for detecting AI-generated videos. Additionally, to rigorously evaluate the cross-domain generalization of detection models, we construct a high-quality and challenging video forgery detection benchmark (i.e., **Closed Benchmark**) entirely generated by commercial models that *share no overlap* with the generation methods in the training datasets.

Building on the GenBuster-200K, we propose **BusterX**, a novel MLLM-based video forgery detection and explanation framework with reinforcement learning strategy. Specifically, the inspiration for BusterX stems from treating AI-generated video detection as a **Visual Reasoning** task rather than merely a binary classification task. We are convinced that this shift in perspective enables a deeper exploration of the intrinsic logic and connections within video frames, thereby achieving more accurate and interpretable detection results. To this end, we employ the reinforcement learning strategy to train our reasoning model, enabling it to perform step-by-step reasoning. This approach not only significantly enhances the interpretability of the detection results but also provides a clear logical chain for the model’s decision-making process, allowing it to explain each judgment in a manner that is understandable to humans.

Building upon pre-trained Qwen2.5-VL-7B [7] as our base model, we pursue two key goals: **1)** video authenticity detection and **2)** generation of human-aligned textual rationales that explain these judgments. Crucially, our reinforcement learning implementation enables the model to achieve strong explanatory performance using only binary

labels (**REAL/FAKE**). This paradigm strategically avoids the need for extensive manual annotations for explanatory text, substantially saving the annotation costs. As the baseline model for GenBuster-200K, BusterX advances both performance and transparency in synthetic video detection.

The contributions of this paper are: **1)** We present **GenBuster-200K**, the first large-scale, high-quality AI-generated video dataset with the latest generative models. It effectively addresses the authenticity, scope, and fairness limitations of previous datasets. **2)** We introduce **BusterX**, the first MLLM-based video forgery detection and explanation framework with reinforcement learning strategy, tailored to identify videos while providing decision-making explanation insights, which boosts reliability and real-world applicability. **3)** BusterX achieves new state-of-the-art performance on multiple datasets. Remarkably, BusterX surpasses all the existing methods by at least **3.5%** on the GenBuster-200K test set, **5.5%** on the Closed Benchmark, and **12%** on the FakeAVCeleb dataset [25] in accuracy.

## 2. Related work

### 2.1. AI-Generated Video Detection Dataset

Early datasets primarily focused on face manipulation and generation, typically employing GANs, VAEs, or various swapping techniques to produce synthetic videos. Datasets such as FaceForensics++ [43], AVCeleb [25], WildDeepfake [68], and KoDF [28] are categorized as deepfake video detection dataset [37]. In recent years, identity-driven forgery datasets have also emerged, with IDFForge [59] being a representative example, which includes various manipulations across visual, audio, and textual modalities.

Recent advances in generative technology have significantly improved the quality of video generation, expanding synthetic content beyond facial manipulations to encompass full-scene natural video synthesis. This shift has broadened the research focus from facial forgeries to holistic video generation, driving the development of diverse datasets for AI-generated video detection. For instance, GenVideo [10] and GenVidBench [37] are large-scale benchmarks built on multiple AI generation models, covering a diverse range of semantic content. However, as Table 1 shows, they are often limited by issues such as relatively low high-quality and diversity, as well as insufficient alignment with real-world contexts. In contrast, GenBuster-200K addresses these challenges by offering higher-quality data, a larger volume, a broader variety of scenarios, and a stronger focus on real-world applicability.

### 2.2. AI-Generated Video Detection Method

Previous methods [18, 38, 49, 50, 56, 57] primarily formulated AI-generated content detection as a binary classification problem, focusing mainly on image-based deepfake de-

Table 1. Comparison with existing AI-Generated video datasets.

Dataset	Latest Model	Scale	High Quality	Efficient Encoding	Resolution	FPS	Diversity	Real-World Scenes
GVD [6]	2024/01	11k	✗	✗	Variable	-	-	-
GVF [35]	2024/03	2.8k	✗	✗	Variable	-	-	-
GenVideo [10]	2024/04	2271k	✗	✗	Variable	8-24	-	-
GenVidBench [37]	2024/04	143k	✗	✗	Variable	3-30	-	-
GenBuster-200K	<b>2025/01</b>	200k	✓	✓	1024x1024	24	✓	✓

tection. These methods utilized various architectures, such as CNNs and Transformers. To enhance the interpretability of the models, Huang et al. [22] recently propose a method for localizing altered regions in images and generating textual explanations, with a specific emphasis on detecting image editing manipulations.

As AI-generated video quality advances, the demand for robust detection methods grows increasingly urgent. Early works primarily focused on face-centric deepfake detection [11, 12, 40, 67]. For instance, Zheng et al. [12, 67] develop methods that identify spatial inconsistencies to distinguish real from synthetic content. Meanwhile, Pellicer et al. [40] propose a model that learns person-specific prototypes by analyzing patterns in real videos. However, these methods struggle to generalize to in-the-wild AI-generated video detection. To address these limitations, recent works have explored alternative strategies. DeMamba [10] detects synthetic videos by analyzing small spatiotemporal zones, capturing subtle pixel changes. UNITE [27] enhances synthetic video detection by capturing full-frame manipulations using a transformer-based architecture with domain-agnostic features. Reiss et al. [42] propose the concept of fact-checking for detection and introduce FACTOR, a practical recipe that effectively counters critical attacks such as face swapping and audio-visual synthesis. To address these challenges, BusterX not only detects video authenticity but also provides detailed explanations by treating AI-generated video detection as a visual reasoning task, thereby enhancing the analysis of AI-generated content detection.

### 2.3. Multimodal Large Language Model

Since the emergence of large language models (LLM), like GPT-4 [2] and Gemini [52], their remarkable success across various language-related tasks has facilitated the advancement of multimodal large language models (MLLM), which integrate both vision and language modalities. MLLMs have evolved significantly, progressing from early vision-language models to large-scale autoregressive frameworks that integrate multiple modalities. Initial approaches, such as CLIP [41] and ALIGN [23], employ contrastive learning to align vision and language representations in a shared embedding space, enabling zero-shot image-text retrieval and

classification. Subsequent models, including BLIP [29] and Flamingo [4], introduce more sophisticated vision-language pretraining strategies, incorporating retrieval-augmented learning and cross-attention mechanisms to improve contextual understanding. BLIP-2 [30] and LLaVA [32] have integrated vision encoders with large autoregressive language models, enabling image-conditioned text generation and multimodal reasoning.

Qwen2.5-VL [8] further advances these developments by improving vision-language alignment through a more efficient vision encoder and enhanced cross-modal fusion mechanisms. There has been a growing interest in leveraging MLLMs for fine-grained pixel-level understanding tasks, like Pixel-SAIL [66] and Sa2VA [65]. Recently, the integration of MLLM has introduced a new paradigm in image deepfake detection. Models such as AntifakePrompt [9], ForgeryGPT [33], FakeShield [61], ForgeryTalker [31], ForgerySleuth [48] and SIDA [22] utilize the capabilities of MLLM to enhance detection accuracy and provide robust support for localization and explanation tasks.

Reinforcement Learning from Human Feedback (RLHF) has demonstrated its effectiveness in enhancing LLM reasoning capabilities [2, 52] after the Supervised Fine-Tuning (SFT) stage [34]. DeepSeek-R1 [16] introduces Group Relative Policy Optimization (GRPO), a variant of RL algorithm of Proximal Policy Optimization (PPO) [45], to improve model performance in reasoning [46]. The community has also made numerous attempts to improve GRPO. For instance, the DAPO (Decoupled Clip and Dynamic sAmpling Policy Optimization) [64] and DanceGRPO [62] are recent efforts in this direction. To enable the model to not only classify videos as real or fake but also provide explanations that align with human understanding, we apply the RLHF strategy to the video forgery detection task, which represents the first attempt in this research domain.

## 3. Benchmark

### 3.1. Motivation

In the field of AI-generated detection, research has primarily focused on facial data due to its significant societal impact. However, with the rapid advancement of generative models,

Table 2. Data distribution for the GenBuster-200K.

Model	Release Date	Train Set	Test Set	Closed Benchmark
Real	-	100k	1000	1000
EasyAnimateV5.1 [60]	2025/01	40k	400	-
HunyuanVideo [26]	2024/12	10k	100	-
CogVideoX [63]	2024/08	30k	300	-
LTX-Video [19]	2024/12	20k	200	-
Commercial AIGC Models	-	-	-	1000

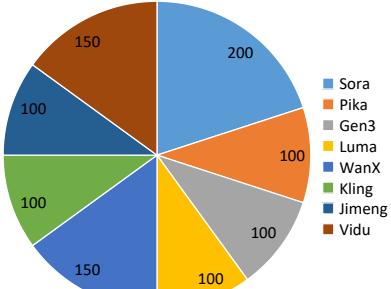


Figure 1. Commercial models and data composition in the closed benchmark.

attention has increasingly shifted toward wider AI-generated video content, which poses broader challenges and risks. Historically, non-facial AI-generated video datasets are rare due to technological limits that made them low-quality and easily detectable. Although datasets such as GenVideo [10] and GenVidBench [37] have been developed, they exhibit several limitations. **1)** These datasets frequently employ outdated generative techniques, resulting in relatively lower-quality data that remain easily distinguishable by human observers. **2)** These datasets exhibit limited diversity in synthesis techniques and source content, which restricts the generalizability of models to real-world scenarios and reduces their effectiveness in assessing detection performance across diverse manipulations. **3)** These datasets do not focus on real-world scenarios. This not only limits their ability to reflect practical forgery situations but also constrains their effectiveness in offering interpretative insights.

### 3.2. Benchmark Construction

**Data Sources:** Our dataset, GenBuster-200K, consists of two parts: real videos from real-world scenarios and synthetic videos that simulate real-world conditions. The details are as follows:

**Real Videos.** More than 100K real videos sourced from OpenVid-1M [36], covering a diverse range of real-world scenarios. These videos were carefully filtered to ensure high quality and eliminate any duplicate clips.

**Synthetic Videos Generation.** More than 100K videos were generated with high realism and diversity. We developed Multi-dimensional Controlled Prompt Pipeline (MCPP) and experimented with several state-of-the-art generative models, including open-source models, such as Hunyuan-Video [26] and LTX-Video [19], and commercial models

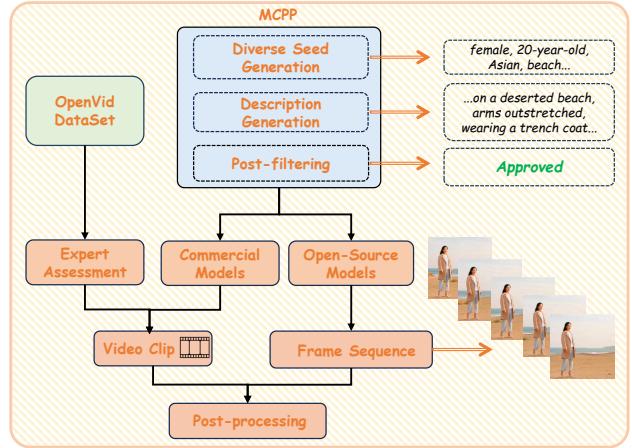


Figure 2. Video generation and collection pipeline.

accessible via APIs, such as Sora [39] and Jimeng [1]. For each model, we generated video frames at various resolutions and with different hyper-parameters to ensure diversity.

**Synthetic Data Generation Pipeline:** Figure 2 illustrates our synthetic video generation pipeline. The main process, contained within MCPP, comprises three stages:

**Stage-1: Diverse Seed Generation.** This stage involves collecting keywords to encompass a wide variety of scenarios, with particular attention to human-related contexts. We systematically account for diversity across gender, age, ethnicity, and other key attributes to maintain balanced representation. Beyond human-centric terms, we also incorporate keywords from diverse domains, such as animals, sceneries, and other non-human contexts, to broaden the semantic scope. This methodical approach ensures our initial semantic space is both inclusive and comprehensive, spanning a wide range of subjects and perspectives.

**Stage-2: Description Generation.** Building on the prior output from stage-1, the forthcoming synthetic video descriptions will be generated by an LLM using a predefined prompt. Specifically, the process includes: **1) Prompt Constraints Guidance:** The system prompt introduces physical and aesthetic constraints. Example dialog templates are based on content understanding of common real videos using VLM, with manual adjustments to cover multiple scenarios. These constraints guide the LLM to generate descriptions that are both realistic and contextually appropriate. **2) Multi-model Overfitting Resistance:** To combat model-specific bias, we randomly sample from a diverse pool of over 20 open-source LLMs, spanning varied architectures and parameter scales (e.g., DeepSeek-V3 [15], LLaMA [55], etc.). Additionally, we employ high-temperature sampling to maximize output diversity during generation.

**Stage-3: Post-filtering.** After generating the prompt, we employ a multi-step post-filtering mechanism to ensure the quality and reliability of the generated prompts. Specifically,

the post-filtering process includes the following key steps: **1) Length Control:** We first check the length of each generated prompt to ensure it falls within a predefined range. Prompts that are too short may lack sufficient context, while those that are excessively long can introduce unnecessary complexity or redundancy. **2) Special Character Check:** We then scan for any special characters or formatting issues that may have been inadvertently introduced during the generation process. **3) Readability Scoring:** The LLM Judge assigns a readability score based on linguistic coherence, grammatical correctness, and overall clarity. Prompts with scores below a predefined threshold are discarded to ensure that only high-quality prompts are retained. By integrating these steps, we can ensure that the generated prompts are of high quality.

**Post-processing.** We perform unified post-processing on both the generated video frames and the selected real videos. This process standardizes the resolution to  $1024 \times 1024$ , the duration to 5 seconds, and the frame rate to 24 FPS. This ensures consistency across videos generated by different models, which may have varying original resolutions and frame rates.

Additionally, we employ HEVC encoding using x265 with default parameters to encode the videos in the yuv420p10le format. This achieves a better balance between file size and video quality, allowing for higher video quality at the same bitrate. The unified post-processing eliminates potential biases from underlying encoding preferences (e.g., commonly used x264), which is crucial for ensuring the generalizability of forgery detection models across diverse video sources.

Table 2 shows the data distribution of GenBuster-200K, which comprises **two** data sources: a dataset with open-source AIGC models and a **Closed Benchmark** with 8 commercial AIGC models (details are shown in Figure 1). The test set is designated to evaluate *in-domain* performance. Notably, these videos in the test set are generated at **higher specifications** to increase the difficulty and are selected by human experts to ensure their quality and complexity. During model training, only the training set from the open-source dataset is utilized. Consequently, Closed Benchmark serves as an unseen-domain set to evaluate the model’s *cross-domain* generalization capability. The entire process consumed over 10,000 A100 GPU hours. To ensure the realism and quality of synthetic videos, we engaged 5 annotation experts for quality control and adjustments. Moreover, for the commercial models without accessible APIs, we manually generate videos by interacting with web interfaces.

## 4. Method

In this section, we introduce BusterX, a novel framework for detecting AI-generated videos and providing detailed explanations. We train a reasoning MLLM with Chain of Thought (CoT), which enables the model to perform step-by-

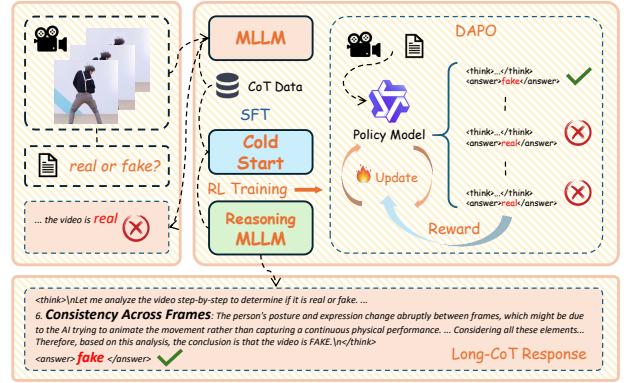


Figure 3. The BusterX framework uses MLLM to analyze a video and determine if it is AI-generated, providing reasoning for its decision. Full response details are in the appendix.

step reasoning, significantly enhancing the interpretability of the detection results. Unlike traditional deepfake detection techniques that depend on reference videos, BusterX operates without such references, substantially improving its practical applications.

### 4.1. Multi-Stage Training

As shown in Figure 3, BusterX’s training involves two stages: Cold Start and RL Training. We use Qwen2.5-VL-7B [7] as the base model, which enhances spatial understanding by using raw coordinates and improves temporal modeling via dynamic FPS training and absolute time encoding—features well aligned with our task. Prompt details are provided in the appendix.

**Cold Start.** We adopt Prompt-Tuning to collect 10k short CoT data samples from the base model. We filter and format the data, ensuring that the positive and negative samples are balanced at a ratio of 1:1. Then, we use the collected data to perform a rapid Cold Start using Supervised Fine-Tuning (SFT). This initial training phase helps the model quickly learn the answer format.

**RL Training.** After the Cold Start phase, we proceed with Reinforcement Learning (RL) training to further refine the model’s ability to produce detailed and high-quality explanations.

In our implementation, we employ LoRA (Low-Rank Adaptation) [21] to boost efficiency. By integrating low-rank trainable matrices into the model’s layers, LoRA enables efficient SFT while retaining the original pre-trained weights. This strategy significantly reduces the number of trainable parameters, and in our experiments, only about 0.66% of the total parameters need to be trained.

### 4.2. Reward Functions

We adopt DAPO [64] as our reinforcement learning strategy, as its core techniques align well with our goal of generating reasonable and interpretable outputs. DAPO incorporates

Table 3. Comparison with SOTA methods on GenBuster-200K dataset. Bold is the best value.

Methods	Zero Shot	Test Set				Closed Benchmark							
		ACC	F1 Score	Sora	Pika	Gen3	Luma	WanX	Kling	Jimeng	Vidu	Avg-ACC	Avg-F1
3D ResNet [20]	-	70.6	73.5	41.0	77.0	46.0	43.0	61.3	24.0	33.0	58.0	65.6	70.6
3D ResNeXt [20]	-	72.6	75.5	31.0	75.0	39.0	42.0	48.7	22.0	65.0	46.0	65.1	71.0
Vivit [5]	-	78.5	81.2	74.0	52.0	69.0	53.0	62.0	55.0	33.0	68.7	76.2	79.4
VideoMAE [54]	-	79.1	81.7	48.5	79.0	65.0	52.0	76.7	24.0	55.0	72.0	76.9	80.3
DeMamba [10]	-	82.0	83.9	65.0	75.0	73.0	56.0	46.0	68.0	71.0	<b>84.7</b>	79.3	82.0
Qwen2.5-VL-7B [7]	✓	51.5	64.1	3.0	14.0	10.0	13.0	8.7	3.0	3.0	4.7	52.4	64.8
Qwen2.5-VL-7B [7]	-	72.8	71.2	75.0	71.0	75.0	75.0	76.0	71.0	76.0	58.0	74.7	74.6
Ours	-	<b>85.5</b>	<b>85.5</b>	<b>81.5</b>	<b>81.0</b>	<b>82.0</b>	<b>82.0</b>	<b>88.7</b>	<b>81.0</b>	<b>82.0</b>	82.0	<b>84.8</b>	<b>85.1</b>

Table 4. Comparison with existing related works on FakeAVCeleb.

Method	AUC	ACC
MesoI4 [3]	75.8	72.2
EfficientNet [51]	-	81.0
Xception [44]	76.2	71.7
FTCN [67]	64.9	84.0
ICT [17]	63.9	68.2
ICT-Ref [17]	64.5	71.9
ID-Reveal [13]	60.3	70.2
Ours	-	<b>96.3</b>

several key methods—including clip-higher, dynamic sampling, token-level policy gradient loss, and overlong reward shaping—all designed to enhance learning efficiency and output quality. Specifically, DAPO samples multiple responses for each question, computes relative advantages using predefined reward functions, and updates the policy to maximize rewards. We design the following reward functions:

**Format:** If the model adheres to the specified format (i.e., <think>...</think>and <answer>...</answer>), it receives a reward of  $r_{\text{fmt}} = 0$ ; otherwise, it receives a penalty of  $r_{\text{fmt}} = -1$ .

**Soft Overlong:** When the response length exceeds the maximum value, we define a penalty interval.

$$r_{\text{overlong}} = \begin{cases} 0, & L_{\text{gen}} \leq L_{\text{max}} - L_{\text{cache}} \\ \frac{(L_{\text{max}} - L_{\text{cache}}) - L_{\text{gen}}}{L_{\text{cache}}}, & L_{\text{max}} - L_{\text{cache}} < L_{\text{gen}} \leq L_{\text{max}} \\ -1, & L_{\text{max}} < L_{\text{gen}} \end{cases} \quad (1)$$

**Accuracy-Based Length:** If the model classifies correctly and follows the format, it receives a reward of  $\frac{L_{\text{gen}}}{L_{\text{max}}}$ ; otherwise,  $r_{\text{len}} = 0$ .

The total reward is computed as  $R = r_{\text{fmt}} + r_{\text{overlong}} + r_{\text{len}}$ .

As shown in Figure 4, without the length reward mechanism, the model fails to generate sufficiently long CoT responses. In our task, long CoT is crucial for fostering deeper video reasoning capabilities. However, naively encouraging

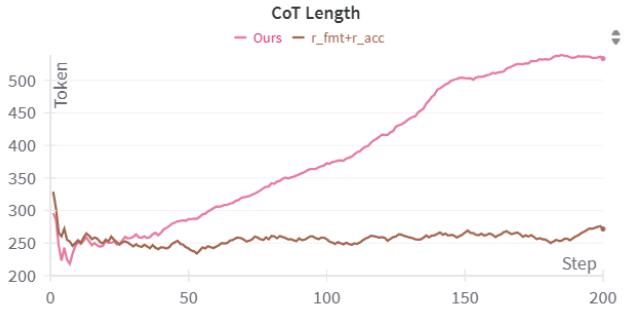


Figure 4. CoT Length comparison across different reward functions.

longer outputs risks producing excessively verbose answers, which both squander computational resources and destabilize training. To mitigate this, we propose a soft overlength penalty. By strategically balancing these opposing objectives, we maintain responses within an optimal length range. This approach ensures the generation of thorough explanations while preserving training stability, ultimately yielding more interpretable results.

## 5. Experiments

### 5.1. Experimental Details and Evaluations

**Implementation Details.** We resized video frames to a resolution of 256x256 and uniformly sampled 16 frames at a rate of 4 FPS for video-level detection. For both models, we employed LoRA with a rank of 16 and alpha of 32, and trained using a learning rate of  $1 \times 10^{-5}$ , which was empirically determined to provide a good balance between convergence speed and model performance. We used bfloat16 for training to optimize computational efficiency. The baseline models used for comparison were trained with default settings from their original papers. In addition to fine-tuning, we also evaluated the zero-shot capabilities of several MLLMs to assess their performance.

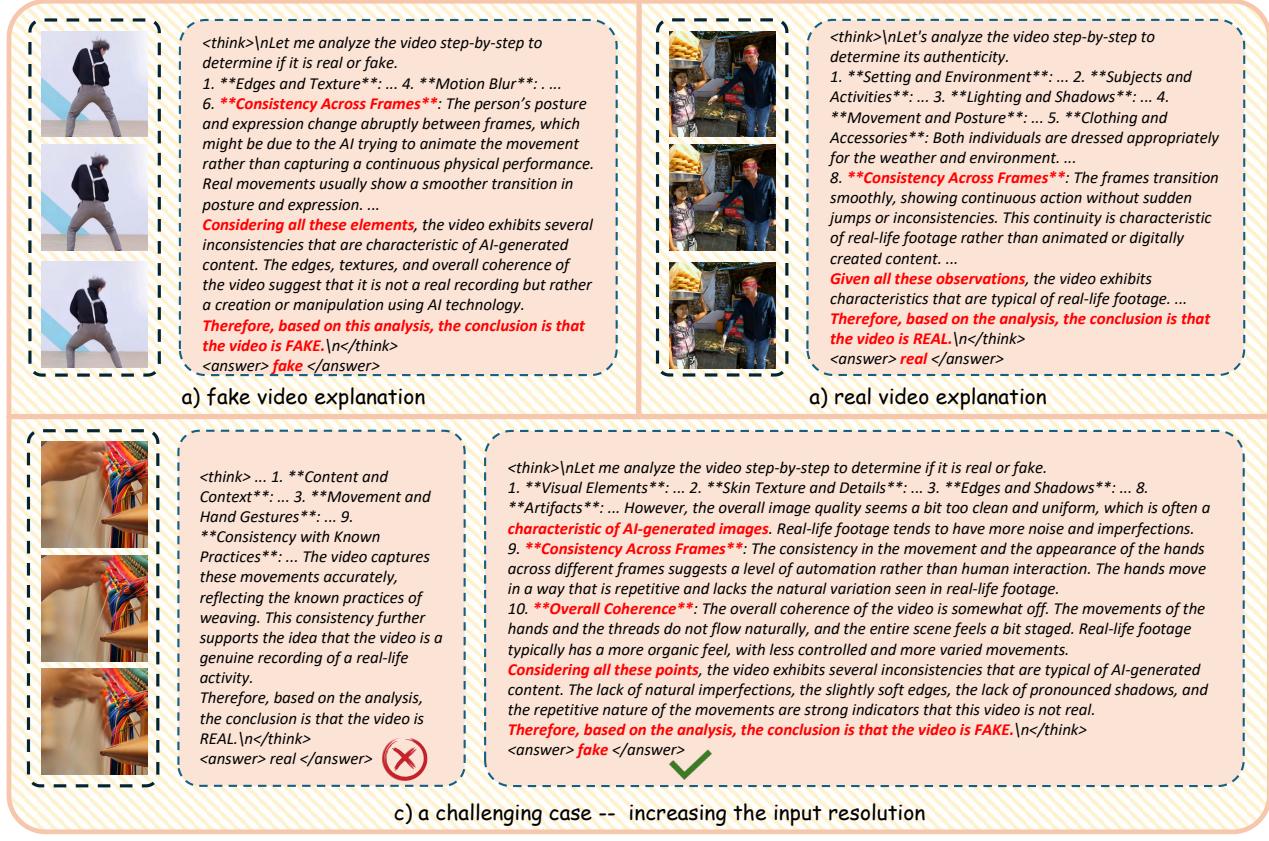


Figure 5. Case Study. Full responses are provided in appendix.

**Evaluation Metrics.** To comprehensively evaluate the performance of our models, we used ACC (accuracy) and F1 score to measure the model’s ability. Additionally, for Closed Benchmark subsets that only contain fake videos, we calculated the ACC separately.

## 5.2. Performance Comparison on GenBuster-200K

We tested the performance of BusterX across different data distributions to evaluate the model’s generalization ability to unseen generators, thereby providing a robust assessment of its real-world applicability. In comparison with other methods, including 3D ResNet, ResNeXt (152-layer) [20], Vivit [5], VideoMAE [54], DeMamba [10] and some MLLMs, BusterX consistently delivers superior ACC and F1 scores across both Test Set and Benchmark, as shown in Table 3. Its ability to generalize effectively to unseen commercial models in Benchmark further demonstrated its robustness and adaptability. BusterX’s overall strong performance across multiple subsets indicates its ability to handle a wide range of synthetic content effectively.

## 5.3. Performance on Other Benchmark

While BusterX excels in AI-generated content detection, we evaluate its performance on deepfake detection to showcase

its transferability across diverse manipulation domains, comparing it with other approaches in FakeAVCeleb dataset [25]. This expansion highlights the model’s adaptability to evolving challenges in media manipulation. We selected state-of-the-art (SOTA) visual-only methods evaluated in ID-Forge [59], including MesoInception4 [3], EfficientNet [51], Xception [44], FTCN [67], ICT [17], ICT-Ref [17], and ID-Reveal [13] for our experiments. The results in Table 4 show that BusterX achieves 12% improvement in ACC among visual-only SOTA deepfake detection methods, demonstrating its ability to deliver superior results across a broader range of tasks.

Table 5. Robustness evaluation of BusterX.

Method	Test Set		Closed Benchmark	
	ACC	F1 Score	Avg-ACC	Avg-F1
50% Frame	84.5	85.2	84.4	84.6
2.0 FPS	85.0	84.9	84.5	84.8
JPEG 90	83.5	83.5	82.9	82.8
JPEG 80	82.2	82.1	80.2	80.1
Gaussian 10	82.7	82.6	83.9	83.8
Ours	85.5	85.5	84.8	85.1

## 5.4. Robustness Study

We further assessed the robustness of BusterX against common video perturbations to simulate real-world scenarios, including JPEG compression, Gaussian noise, reducing the number of sampled frames, and increasing the sampling interval. As shown in Table 5, BusterX demonstrates significant resilience to low-level distortions, even without specific training on degraded data. This ability to sustain consistent performance under challenging conditions highlights its robustness and practical value in varied, unpredictable settings.

Table 6. Ablation Study for different training strategies.

Strategy		Test Set		Closed Benchmark		Long
SFT	RL	ACC	F1 Score	Avg-ACC	Avg-F1	CoT
✗	✗	51.5	64.1	52.4	64.8	✗
✓	✗	80.2	80.8	74.1	77.0	✗
✓	✓	85.5	85.5	84.8	85.1	✓

## 5.5. Ablation Study

In the ablation study, we evaluated the effectiveness of different training strategies. The average scores are calculated to quantify the performance. Table 6 presents the assessment results of explanatory capabilities. Statistical findings reveal that RL training significantly enhances the performance of the model, enabling BusterX to produce more reasonable explanations.

## 5.6. Case Study

We provide a set of responses to demonstrate the model’s performance in Figure 5. We have some interesting findings from BusterX’s explanations. **1) Consistent reasoning and step-by-step analysis:** The reasoning process enables the model to thoroughly analyze the visual evidence and summarize its findings. **2) Robust interframe relationship capture:** The model examine frame transitions and identify inconsistencies. **3) Attention to low-level details:** The model can detect subtle anomalies such as unnatural motion blur. More results are available in the appendix.

In real video analysis, the model meticulously examined the transitions between frames and found them to be seamless and natural, with continuous action and consistent environmental details. When analyzing the fake video, the model’s attention to interframe anomalies proved decisive. It detected abrupt changes and inconsistencies in the subject’s posture and expression between frames, which are telltale signs of digital manipulation or AI generation. However, we observed that some video clips remain challenging. We found that increasing the input resolution can improve the results by helping the model better capture finer details within the video frames. Despite these challenges, the model’s per-

formance in the case studies highlights its advanced visual reasoning ability.

## 6. Conclusion and Limitations

In this paper, we present GenBuster-200K, a large-scale dataset comprising 100K real videos and 100K AI-generated videos. Building on GenBuster-200K, we propose BusterX, a novel MLLM framework to detect and explain AI-generated videos. As the first framework capable of providing detailed explanations, BusterX sets a new standard by enhancing the interpretability of AI-generated video detection. Despite promising progress, we recognize certain limitations and aim to address them through future optimization. **1) Data modality.** Our dataset currently includes video only, while AI-generated content spans multiple modalities (e.g., audio, subtitles). Incorporating these is a key future goal. **2) Dataset Scale.** Real-world complexity demands a larger dataset. Expanding video coverage is essential to improve detection robustness and generalizability.

## A. Visual Examples

Figure 6 presents a selection of video examples from GenBuster-200K, showcasing its high-quality and diversity.



Figure 6. Visual Examples from GenBuster-200K.

## B. DAPO

We utilize DAPO [64] as our reinforcement learning strategy. DAPO samples a group of outputs  $\{o_i\}_{i=1}^G$  for each question  $q$  from the old policy  $\pi_{\theta_{old}}$ . The reward model is then used to score the outputs, yielding  $\{r_i\}_{i=1}^G$  correspondingly. Then DAPO optimizes the policy model  $\pi_\theta$  by maximizing the following objective:

$$\begin{aligned}
\mathcal{J}_{\text{DAPO}}(\theta) = & \mathbb{E}_{(q,a) \sim \mathcal{D}, \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)} \\
& \left[ \frac{1}{\sum_{i=1}^G |o_i|} \sum_{i=1}^G \sum_{t=1}^{|o_i|} \min \left( r_{i,t}(\theta) \hat{A}_{i,t}, \text{clip} \left( r_{i,t}(\theta), 1 - \varepsilon_{\text{low}}, 1 + \varepsilon_{\text{high}} \right) \hat{A}_{i,t} \right) \right] \\
\text{s.t. } & 0 < \left| \{o_i \mid \text{is\_equivalent}(a, o_i)\} \right| < G,
\end{aligned} \tag{2}$$

where  $\varepsilon_{\text{low}}$  and  $\varepsilon_{\text{high}}$  are hyper-parameters, and  $\hat{A}_{i,t}$  is the advantage:

$$r_{i,t}(\theta) = \frac{\pi_\theta(o_{i,t} \mid q, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid q, o_{i,<t})}, \quad \hat{A}_{i,t} = \frac{r_i - \text{mean}(\{r_i\}_{i=1}^G)}{\text{std}(\{r_i\}_{i=1}^G)}. \tag{3}$$

### C. CoT Length

In our experiments, we extensively explored the optimal settings for CoT to strike a balance between training stability and the model's ability to perform frame-level reasoning. We discovered that overly long CoT responses tend to destabilize training, leading to erratic performance and increased computational overhead. Conversely, excessively short CoT responses fail to capture the necessary reasoning steps required for frame-level inference, resulting in superficial or inaccurate explanations.

To address this challenge, we conducted numerous experiments to identify the ideal CoT length. We found that setting the maximum length  $L_{\text{max}}$  to 2048 tokens and the cache length  $L_{\text{cache}}$  to 1448 tokens yielded the best results. This configuration aims to maintain an expected CoT length of around 600 tokens, which is sufficient for detailed reasoning while avoiding excessive verbosity.

### D. Prompt Design

Based on some experiments, we have carefully designed the following prompts to guide the answer.

#### System Prompt

*A conversation between User and Assistant. The user asks a question, and the Assistant solves it. The assistant first thinks about the reasoning process in the mind and then provides the user with the answer. The reasoning process and answer are enclosed within <think> </think> and <answer> </answer> tags, respectively, i.e., <think> reasoning process here </think><answer> answer here </answer>*

#### User Prompt

*Please carefully describe the content of this video, analyze whether there are any inconsistencies or obvious signs of forgery. Additionally, the low-level features or artifacts that are present in the video can be used to determine if the video is real or fake. Then summarize your analysis with a brief explanation, determining if the video is real or generated/edited by AI. After your analysis, answer with real or fake*

## E. Complete Responses

The model's full responses in Figure 3 and 5.



REAL

<think>

Let's analyze the video step-by-step to determine its authenticity.

1. **Setting and Environment\*\*:** The video depicts an outdoor scene with a makeshift stall, likely in a market or street setting. The background includes colorful tarps and various items for sale, such as boxes and what appears to be food products. The environment suggests a casual, everyday scenario, which is consistent with real-life footage.
2. **Subjects and Activities\*\*:** There are two individuals in the frame. One person is carrying a large tray of food on their head, while the other stands nearby, seemingly engaged in conversation or interaction. The person carrying the tray is dressed in traditional attire, which could indicate a cultural context. The second individual is wearing modern clothing, suggesting a contrast in roles or purposes. This diversity in attire adds to the realism of the scene.
3. **Lighting and Shadows\*\*:** The lighting appears natural, with shadows that align with the direction of the sun. The shadows cast by the individuals and objects are consistent with the time of day, indicating that the video was likely taken during daylight hours. There are no artificial light sources or unusual shadow patterns that would suggest digital manipulation.
4. **Movement and Posture\*\*:** The movements of the individuals are fluid and natural. The person carrying the tray balances it steadily, and the standing individual gestures naturally, which is typical of real-life interactions. There are no abrupt or unnatural movements that would indicate the use of special effects or animation.
5. **Clothing and Accessories\*\*:** Both individuals are dressed appropriately for the weather and environment. The person carrying the tray wears a headscarf and patterned clothing, which could be indicative of local customs. The other individual wears jeans and a jacket, which is suitable for cooler weather. The clothing does not appear exaggerated or out of place, supporting the idea that this is a genuine recording.
6. **Background Elements\*\*:** The background includes various items for sale, such as boxes and what looks like food products. These elements are consistent with a market or street vendor setup. The presence of these items adds context to the scene and enhances the realism of the video.
7. **Video Quality\*\*:** The video quality appears natural without any visible artifacts or distortions. The colors are vibrant yet realistic, and there are no signs of digital enhancement or compression artifacts. The clarity of the image allows for detailed observation of the subjects and their surroundings.
8. **Consistency Across Frames\*\*:** The frames transition smoothly, showing continuous action without sudden jumps or inconsistencies. This continuity is characteristic of real-life footage rather than animated or digitally created content.
9. **Absence of Digital Anomalies\*\*:** There are no visible seams, inconsistencies in texture, or other telltale signs of digital manipulation. The overall coherence of the video, including the natural movement, lighting, and environmental details, supports the authenticity of the footage.
10. **Cultural Context\*\*:** The scene includes elements that are common in many parts of the world where street vendors and markets are prevalent. The attire, the type of food being carried, and the general atmosphere are consistent with real-life observations in such settings.

Given all these observations, the video exhibits characteristics that are typical of real-life footage. The natural setting, realistic movements, consistent lighting, and absence of digital anomalies all point towards the video being an authentic recording rather than a fabricated or edited piece.

Therefore, based on the analysis, the conclusion is that the video is REAL.

</think>

<answer>

real

</answer>



FAKE

<think>

Let me analyze the video step-by-step to determine if it is real or fake.

1. **Edges and Texture**: Upon close inspection, the edges of the person's clothing appear somewhat smooth and lack the sharpness one would expect from a real photograph. The fabric texture does not show the natural wrinkles and folds that would be present in real-life clothing. This suggests that the image might have been digitally altered or created using AI.
2. **Skin Texture**: The person's skin appears too smooth, lacking the natural imperfections such as pores and slight blemishes that are typically seen in real individuals. This is a common sign of AI-generated images, where the skin is often rendered with a high level of detail but lacks the subtleties found in human skin.
3. **Background and Depth**: The background is quite plain and lacks the depth and complexity one would expect in a real-world setting. There are no distinct shadows or highlights that would suggest a three-dimensional environment. The lighting on the person is even across their face and body, which is unusual for a real-life scenario where lighting would vary based on the time of day and surrounding environment.
4. **Motion Blur**: The person appears to be mid-jump, but the motion blur is not consistent with what you'd see in a real jump. The legs and arms seem to freeze mid-air, which is not typical of natural motion. This could indicate that the jump was either slowed down significantly or the animation was not done correctly.
5. **Artifacts and Compression**: There are no visible artifacts or signs of compression that would suggest the video was heavily edited. However, the overall image quality seems slightly off, lacking the crispness and clarity one would expect from a high-quality real video.
6. **Consistency Across Frames**: The person's posture and expression change abruptly between frames, which might be due to the AI trying to animate the movement rather than capturing a continuous physical performance. Real movements usually show a smoother transition in posture and expression.
7. **Overall Coherence**: The entire sequence feels slightly off-kilter. The combination of the smooth edges, uniform skin texture, and lack of natural imperfections, along with the inconsistent motion blur, points towards the use of AI for generation or editing. Considering all these elements, the video exhibits several inconsistencies that are characteristic of AI-generated content. The edges, textures, and overall coherence of the video suggest that it is not a real recording but rather a creation or manipulation using AI technology.

Therefore, based on this analysis, the conclusion is that the video is FAKE.

</think>

<answer>

**fake**

</answer>



### A Challenging Case – In the case of low-resolution input, the response was incorrect.

<think>

Let's analyze the video step-by-step to determine its authenticity.

1. **Content and Context**: The video depicts hands engaged in weaving, specifically working with colorful threads on a loom. This activity is a common craft practice, often seen in workshops or homes where individuals create textiles. The focus on the hands and the loom suggests a close-up shot, likely intended to showcase the intricate process of weaving.

2. **Lighting and Shadows**: The lighting appears natural, with soft shadows that suggest indoor lighting. There are no harsh contrasts or overly bright spots that would indicate artificial lighting. The shadows are consistent with the angle of light coming from one side, which is typical for indoor settings.

3. **Movement and Hand Gestures**: The hands move smoothly and purposefully, indicating a skilled action. The way the fingers manipulate the threads and the loom's components is fluid and precise, which is characteristic of someone who is experienced in weaving. There are no abrupt movements or jerks that would suggest digital manipulation or animation.

4. **Background Elements**: The background is slightly blurred, focusing attention on the hands and the loom. This technique is commonly used in close-up shots to emphasize the subject while providing enough context to understand the setting. The background does not show any distinct objects or features that would suggest a specific location, but it is consistent with a workshop or a home environment where such activities take place.

5. **Color and Texture**: The colors of the threads are vibrant and varied, adding to the visual appeal of the scene. The texture of the threads and the loom's weave is visible, indicating a high level of detail. This level of detail is difficult to achieve through digital means without significant effort, suggesting that the video captures a real-life scenario.

6. **Overall Coherence**: The video maintains a coherent narrative throughout. The sequence of actions—threading, pulling, and weaving—is logical and follows the natural progression of the craft. There are no sudden changes in the scene or unexpected elements that would disrupt the flow of the video.

7. **Technical Aspects**: There are no visible artifacts, such as pixelation, blurring, or digital noise, that would suggest the use of special effects or digital editing. The clarity and sharpness of the image are consistent with a real-world recording.

8. **Human Element**: The presence of human hands performing a manual task adds a layer of authenticity. The hands appear to belong to an adult, and the posture and dexterity are those of someone engaged in a skilled activity. There are no signs of digital manipulation that would make the hands look unnatural or exaggerated.

9. **Consistency with Known Practices**: Weaving is a well-documented craft with specific techniques and movements. The video captures these movements accurately, reflecting the known practices of weaving. This consistency further supports the idea that the video is a genuine recording of a real-life activity.

Given all these observations, the video exhibits characteristics that are consistent with a real-life recording. The natural lighting, smooth movements, coherent narrative, and absence of digital artifacts all point towards the video being an authentic depiction of someone weaving.

Therefore, based on the analysis, the conclusion is that the video is REAL.

</think>

<answer>

real

</answer>



A Challenging Case – After increasing the input resolution, the response was correct.

<think>

Let me analyze the video step-by-step to determine if it is real or fake.

1. **Visual Elements**: The video shows hands working on a weaving loom. The threads are vibrant and varied in color, and the hands appear to be manipulating them skillfully. The focus is on the hands and the loom, which suggests a close-up shot.

2. **Skin Texture and Details**: The skin tone of the hands appears somewhat smooth but not entirely unrealistic. There are no visible pores or natural imperfections that one would expect to see in a real-life scenario. This could be a sign of AI generation, as AI often struggles to replicate natural skin textures accurately.

3. **Edges and Shadows**: The edges of the hands and the threads seem slightly soft and not sharply defined. In real-life footage, we typically expect sharper edges and more defined shadows. The softness might be due to the blurring effect often used in AI-generated images to give them a more polished look.

4. **Repetitive Patterns**: There are no obvious repetitive patterns in the video. However, the way the hands move and interact with the threads does not exhibit the kind of fluidity and precision that one would expect from a real person. The movements appear somewhat mechanical, which is a common characteristic of AI-generated images.

5. **Lighting and Shadows**: The lighting on the hands and the threads is consistent, but the shadows cast by the hands are not very pronounced. In real-life footage, shadows tend to be more dynamic and vary depending on the angle of the light source. The lack of strong shadows could be another indicator of AI generation.

6. **Background and Depth**: The background is blurred, which is typical for close-up shots where the focus is on the subject. However, the depth of field seems a bit too perfect, lacking the subtle variations that would be present in a real-world setting. This could be a sign of post-processing or AI manipulation.

7. **Motion Blur**: The hands are in constant motion, and there should be some motion blur, especially around the fingers and the threads. The video does not show any significant motion blur, which could be another indication of AI generation. Real-life footage usually has some degree of motion blur, even in high-speed cameras.

8. **Artifacts**: There are no visible artifacts such as pixelation or blurring in areas that should be sharp. However, the overall image quality seems a bit too clean and uniform, which is often a characteristic of AI-generated images. Real-life footage tends to have more noise and imperfections.

9. **Consistency Across Frames**: The consistency in the movement and the appearance of the hands across different frames suggests a level of automation rather than human interaction. The hands move in a way that is repetitive and lacks the natural variation seen in real-life footage.

10. **Overall Coherence**: The overall coherence of the video is somewhat off. The movements of the hands and the threads do not flow naturally, and the entire scene feels a bit staged. Real-life footage typically has a more organic feel, with less controlled and more varied movements.

Considering all these points, the video exhibits several inconsistencies that are typical of AI-generated content. The lack of natural imperfections, the slightly soft edges, the lack of pronounced shadows, and the repetitive nature of the movements are strong indicators that this video is not real.

Therefore, based on the analysis, the conclusion is that the video is FAKE.

</think>

<answer>

fake

</answer>

## F. Additional Examples



### 1. FAKE

<think>

Let me analyze the video step-by-step to determine if it is real or fake.

1. **Edges and Texture**: The giraffe's legs appear to have a smooth transition into the grass, lacking the natural roughness and texture one would expect from a real animal. The edges of the giraffe's body seem slightly softened, which is not typical for a live animal. The fur texture looks too uniform and lacks the fine details and variations you'd see in a real giraffe.
2. **Background Consistency**: The background consists of a grassy landscape with some trees. However, the trees and grass appear somewhat artificial. There's a lack of depth and detail that you'd expect in a natural setting. The colors are vibrant but lack the subtle variations and gradients you'd see in a real environment.
3. **Lighting and Shadows**: The lighting on the giraffe is even and lacks the dynamic range and shadows that would be present in a real-life scenario. Shadows are present but seem too soft and not sharply defined, which could indicate digital manipulation rather than natural sunlight.
4. **Motion Blur**: The giraffe appears to be moving, but the motion blur is minimal and inconsistent. In a real video, you'd expect to see more pronounced motion blur, especially in the legs and tail, due to the speed and weight of the animal.
5. **Artifacts and Compression**: There are no visible artifacts or signs of compression that would suggest the video was heavily edited. However, the overall image quality seems slightly off, with a slight glow around the edges of the giraffe, which could be indicative of digital enhancement.
6. **Repetitive Patterns**: The background does not show any repetitive patterns that would suggest a fake environment. However, the overall composition feels staged, which is common in AI-generated images.
7. **Depth of Field**: The depth of field appears shallow, focusing primarily on the giraffe while the background is less distinct. This effect is often used in photography and video to draw attention to the subject, but in a real-world scenario, the background would typically have more depth and detail.
8. **Consistency Across Frames**: When comparing different frames, there is a consistent level of detail and color saturation throughout the video. This uniformity is more characteristic of AI-generated images than real footage, where variations in lighting and focus would naturally occur.
9. **Realism of the Scene**: The scene itself looks like a savanna, but the level of detail and the way the giraffe interacts with its environment (e.g., the grass) don't quite match what you'd expect from a real giraffe in its habitat. The giraffe's posture and movement also seem slightly stiff and unnatural.
10. **Overall Coherence**: The video lacks the organic flow and imperfections that would be present in a real video. The giraffe's form is almost too perfect, lacking the subtle imperfections and variations that would be seen in a real animal.

Considering all these points, the video exhibits several inconsistencies that point towards AI generation. The edges, textures, lighting, and overall coherence are not aligned with what we would expect from a real video. Therefore, based on this analysis, the video is FAKE.

</think>

<answer>

fake

</answer>



## 2. FAKE

<think>

Let me analyze the video step-by-step to determine its authenticity.

1. \*\*Edges and Texture\*\*: The edges of the people in the video appear somewhat smooth and lack the sharpness typically seen in real-life footage. This could be a sign of digital manipulation. The textures on the clothing also seem a bit too uniform, lacking the natural wrinkles and folds one would expect from fabric in motion.

2. \*\*Lighting and Shadows\*\*: The lighting appears consistent across the scene, but the shadows cast by the people and objects don't align perfectly with what you'd expect from natural sunlight. Shadows often vary depending on the time of day and the angle of the sun, and the video seems to lack these variations.

3. \*\*Background Details\*\*: The background includes various stalls and hanging fabrics, which appear to be part of a market setting. However, the details in the background are somewhat flat and lack the depth and complexity one would expect in a real market environment. The colors and patterns on the fabrics also seem a bit too uniform and lack the subtle variations you'd see in real-life settings.

4. \*\*Motion and Movement\*\*: The people in the video are moving, but the motion appears somewhat stiff and lacks the fluidity and natural weight shifts one would observe in real-life movements. The way the people interact with each other and the environment also seems a bit staged, lacking the spontaneity typically found in real-world interactions.

5. \*\*Artifacts and Compression\*\*: There are no visible artifacts or signs of compression that would suggest the video was heavily edited. However, the overall image quality does not seem to be high-resolution, which could be due to the nature of the video itself rather than editing.

6. \*\*Consistency Across the Frame\*\*: The consistency in the appearance of the people and the environment suggests a controlled environment rather than a natural setting. The repetition of certain elements, such as the patterned fabrics and the layout of the stalls, gives the impression of a pre-arranged scene rather than a candid capture.

7. \*\*Overall Coherence\*\*: The overall coherence of the scene is somewhat artificial. The arrangement of the people, the positioning of the stalls, and the lighting all seem to work together in a way that feels staged rather than organic. There are no unexpected elements or anomalies that would suggest the video is real.

Considering all these points, the video exhibits several inconsistencies that point towards it being a generated or edited video. The edges, textures, lighting, and overall coherence of the scene all contribute to the conclusion that this is not a real-life recording but rather a digitally created or manipulated video.

Therefore, based on this analysis, the video is FAKE.

</think>

<answer>

fake

</answer>



### 3. REAL

<think>

*Let's analyze the video step-by-step to determine its authenticity.*

1. **Environment and Setting**: The individual appears to be outdoors, likely in a residential area given the presence of a house and greenery in the background. The lighting suggests it is daytime, and the shadows indicate sunlight coming from a specific angle, which is consistent with natural daylight. There are no artificial light sources or reflections that would suggest the use of studio lighting.
2. **Clothing and Appearance**: The person is wearing sunglasses, a denim jacket over a dark shirt, and what seems to be casual attire suitable for outdoor activities. The clothing does not appear exaggerated or out of place for the setting, indicating a natural and unscripted appearance.
3. **Body Language and Movement**: The individual is gesturing with their hands, which suggests they are speaking or explaining something. The movements are fluid and natural, without any stiffness or unnatural motion that might indicate digital manipulation. The posture and hand gestures seem organic and consistent with someone engaged in a conversation or presentation.
4. **Background Elements**: The background includes a house with a white exterior and some greenery, including bushes and trees. These elements are typical of a suburban or residential neighborhood. There are no signs of digital alteration in the background, such as blurred edges or inconsistent textures.
5. **Video Quality**: The video quality appears natural. There are no visible artifacts, such as pixelation or blurring, that would suggest the use of special effects or digital editing. The clarity of the image allows for the distinction of fine details, such as the texture of the denim jacket and the individual's facial features.
6. **Consistency Across Frames**: The frames show a continuous sequence of the individual speaking and gesturing. There are no abrupt changes in the environment or the subject's actions that would indicate a cut from different angles or a staged scene. The consistency in the background and the subject's movements suggests a single take rather than a composite of multiple shots.
7. **Absence of Digital Anomalies**: There are no signs of digital manipulation such as double exposure, inconsistent lighting, or unnatural color grading. The colors and tones in the video are consistent throughout, and the shadows and highlights align with what one would expect from natural lighting conditions.
8. **Contextual Clues**: The context of the video does not provide any clues that suggest it is anything other than a real-life recording. The individual appears to be in a casual setting, possibly sharing information or engaging in a dialogue, which is a common scenario for personal videos or vlogs.

*Given all these observations, the video exhibits characteristics of a genuine recording. The natural lighting, organic movements, consistent background, and absence of digital anomalies all point towards the video being a real-life capture rather than a digitally created or manipulated piece.*

*Therefore, based on the analysis, the conclusion is that the video is REAL.*

</think>

<answer>

real

</answer>



#### 4. REAL

<think>

*Let's analyze the video step-by-step to determine its authenticity.*

1. **Environment and Setting**: The video depicts a snowy landscape with trees covered in frost, indicating a cold climate. The road appears to be clear of snow, suggesting recent plowing or melting. The sky is clear with a gradient from light blue to yellow near the horizon, which could indicate either sunrise or sunset. The trees are bare, which is typical for winter months in many regions. The overall scene looks natural and unaltered.

2. **Lighting and Shadows**: The lighting is soft and diffused, consistent with natural sunlight. Shadows cast by the trees and the road are subtle and realistic, aligning with the time of day suggested by the sky's color. There are no harsh shadows or overly bright spots that would indicate artificial lighting or digital manipulation.

3. **Movement and Activity**: The video shows a person walking on the road. The movement is smooth and natural, with no abrupt changes in posture or gait that might suggest CGI or animation. The person's shadow is present and consistent with the lighting conditions, further supporting the natural appearance of the scene.

4. **Background Elements**: The background consists of trees and a clear sky, with no visible signs of digital manipulation. The trees are uniformly covered in frost, and there are no unnatural elements like floating objects or distorted textures. The road itself is well-defined, with no signs of digital alteration such as seams or inconsistent blending.

5. **Video Quality**: The video does not exhibit any pixelation, blurring, or other artifacts that would suggest it was created using low-quality or compressed footage. The colors are vibrant yet natural, and there are no signs of overexposure or underexposure that would indicate poor lighting conditions during filming.

6. **Consistency Across Frames**: The frames transition smoothly without any sudden jumps or inconsistencies. The environment remains constant throughout the video, with no abrupt changes in weather or lighting that would suggest a cut from different sources or a digitally created scene.

7. **Human Interaction**: The presence of a person walking on the road adds a layer of realism. The individual's clothing and posture are consistent with someone moving through a cold environment, and there are no signs of digital enhancement or manipulation affecting their appearance or behavior.

8. **Overall Coherence**: The entire video maintains a coherent narrative, with no logical inconsistencies or abrupt transitions. The natural elements, including the trees, road, and sky, are all consistent with each other and with the expected appearance of a snowy landscape during what appears to be either early morning or late evening.

Given these observations, there are no significant indicators of digital manipulation or artificial creation. The video appears to be a genuine recording of a real-life scene, capturing a moment in a snowy environment with a person walking on a road.

Therefore, based on the analysis, the video is **REAL**.

</think>

<answer>

real

</answer>

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