
An Evaluation of Hybrid Annotation Workflows on High-Ambiguity Spatiotemporal Video Footage

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Abstract

Manual annotation remains the gold standard for high-quality, dense temporal video datasets, yet it is inherently time-consuming. Vision-language models can aid human annotators and expedite this process. We report on the impact of automatic Pre-Annotations from a tuned encoder on a Human-in-the-Loop labeling workflow for video footage. Quantitative analysis in a study of a single-iteration test involving 18 volunteers demonstrates that our workflow reduced annotation time by 35% for the majority (72%) of the participants. Beyond efficiency, we provide a rigorous framework for benchmarking AI-assisted workflows that quantifies trade-offs between algorithmic speed and the integrity of human verification. Code and collected interaction data are available at [this repository](#).

1. Introduction

Progress in video understanding has been accelerated by large-scale pretraining and, more recently, by Vision-Language Models (VLMs) that align visual content with natural language supervision (Radford et al., 2021; Wang et al., 2022; Zhao et al., 2024). However, for many downstream tasks that require supervised learning methods, including anomaly detection, temporal action localization, and open-world event understanding, the bottleneck remains the same: *dense temporal annotation*.

Unlike static image labeling, video annotation requires defining start and end timestamps for events that unfold over time, often with unclear boundaries, occlusions, and multi-

actor interactions. This makes labeling slow, expensive, and inherently variable between annotators (Uma et al., 2021; Davani et al., 2022). The problem is particularly severe in *high-ambiguity* video footage, where events are not clearly defined and can be regarded as highly subjective, context-dependent, and culturally mediated. At the same time, model development (and fair evaluation) depends on high-quality annotated datasets (Gu et al., 2018; Grauman et al., 2022) and benchmarking (Sultani et al., 2018).

To mitigate labeling cost, the annotation industry has widely adopted Human-in-the-Loop (HITL) workflows: a model proposes *Pre-Annotations* and humans correct them, shifting the annotator’s role from “create” to “verify and refine”. Popular annotation platforms and production tools largely support this paradigm (CVAT.ai Corporation, 2023; Tkachenko et al., 2020). However, despite its prevalence, the research literature lacks rigorous, controlled studies quantifying how AI suggestions affect (i) annotation efficiency, (ii) inter-annotator consistency, and (iii) the semantic integrity of the resulting labels, especially in domains where ambiguity is the norm.

Speed alone is an incomplete objective. AI assistance can reduce time while quietly inducing *semantic drift*. This entails a systematic shift in human labeling toward the model’s priors, potentially reducing the validity of the label even as agreement increases. Prior work has explored ways to reduce human interaction in visual annotation (e.g., verification-centric labeling and interaction-efficient interfaces) (Papadopoulos et al., 2016; 2017; Kuznetsova et al., 2021; Deng et al., 2021; Feng et al., 2023), but there is limited evidence on the human decision dynamics under modern VLM-style Pre-Annotation for *dense temporal* segmentation in open-world footage.

In this work, we present and evaluate a hybrid HITL workflow for dense temporal video segmentation in a deliberately challenging, high-ambiguity setting. We use a resource-efficient cross-modal pipeline, based on a fine-tuned CLIP-style encoder and clustering (Rasheed et al., 2023; Hornik et al., 2012), to generate temporally localized “strong clusters” that serve as Pre-Annotations for humans. Our focus is not on proposing yet another video model, but on provid-

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ing a reproducible *benchmarking framework* for AI-assisted annotation that captures both throughput and label integrity. We conducted a controlled counterbalanced A/B study with 18 annotators labeling videos from open-world datasets, instrumenting the interface to capture rich interaction telemetry (time, edits, label changes, and cluster modifications). Our contributions are:

- **A controlled stress test of AI-assisted dense temporal annotation** in high-ambiguity footage, designed to isolate the effect of Pre-Annotations on human behavior.
- **An end-to-end hybrid workflow** (Pre-Annotation + UI) that is lightweight and reproducible, enabling future work to benchmark human–model interaction under comparable conditions.
- **A multi-axis evaluation protocol** that goes beyond speed, measuring changes in agreement/consensus and latent-space semantic validity, to detect potential semantic drift.
- **A public release of code and anonymized interaction traces** to support reproducibility and follow-up research on human-centric dataset construction.

2. Related Work

AI-assisted annotation and Human-in-the-Loop (HITL). Reducing human labeling costs has long been a practical driver of progress in computer vision. Early work showed that replacing full manual drawing with lightweight verification protocols can substantially reduce the annotation effort (Papadopoulos et al., 2016; 2017). Iterative refinement loops further reinforce the corrective interaction between the model and the annotator (Adhikari & Huttunen, 2021). For video, interaction-efficient systems have explored guidance via interpolation and frame selection (Kuznetsova et al., 2021), single-frame supervision for moment retrieval (Cui et al., 2022), and domain-specific tools to minimize human effort (Deng et al., 2021; Feng et al., 2023; Shrestha et al., 2023). In parallel, production tooling has operationalized model-assisted labeling at scale (e.g., CVAT and Label Studio) (CVAT.ai Corporation, 2023; Tkachenko et al., 2020). Despite this broad adoption, controlled evidence quantifying how Pre-Annotations alter *human* temporal segmentation behavior—beyond throughput—remains comparatively limited, especially in high-ambiguity settings.

Vision-language pretraining for efficient video representations. Vision-language models such as CLIP provide transferable encoders that can be adapted to video tasks with relatively modest computation (Radford et al., 2021). Large-scale video foundation models define strong upper

bounds in representation quality (Wang et al., 2022; Zhao et al., 2024), but are expensive to use as annotation engines. A complementary line of work studies efficient CLIP-style video learners, including frame-level encoding with temporal pooling and targeted finetuning (Rasheed et al., 2023; Wang et al., 2023). Our Pre-Annotation engine follows this resource-conscious philosophy and adds an explicit hierarchical structuring stage using spherical k -means (Hornik et al., 2012) to produce multi-granularity segments. Recursive retrieval methods such as RAPTOR (Sarthi et al., 2024), together with hierarchical video parsing approaches (Cui et al., 2022), provide a principled mechanism that reflects the intrinsic semantic structure of video content.

Anomaly detection and ambiguity. Real-world anomaly detection benchmarks, such as UCF-Crime, are inherently open-ended and temporally ambiguous (Sultani et al., 2018). This ambiguity is compounded by known biases in open-world footage and by models’ tendency to exploit background cues rather than event semantics (Liu et al., 2022). Recent work also explores adapting vision–language models to weakly supervised video anomaly detection (Wu et al., 2024). These characteristics make open-world video a particularly demanding test domain for evaluating whether model suggestions help humans without silently steering them toward model priors.

Quality measurement beyond speed: agreement, drift, and semantics. Annotation tool evaluations often emphasize time-per-label or proxy accuracy metrics (Liao et al., 2021). However, efficiency can mask *semantic drift*: systematic shifts in human boundaries toward the model’s proposed structure. To capture integrity, a common axis is inter-annotator agreement; more recent perspectives argue that disagreement can be meaningful signal rather than noise, especially in subjective tasks (Uma et al., 2021; Davani et al., 2022). We therefore pair agreement/consensus measures with latent-space validity signals inspired by embedding-based evaluation ideas in adjacent areas (Unterthiner et al., 2019; Shahapure & Nicholas, 2020). Finally, transparency frameworks such as CrowdWorkSheets encourage reporting annotator demographics, recruitment, and context to interpret human-centric findings responsibly (Díaz et al., 2022; Gustafson et al., 2023).

3. User Study and Workflow Design

3.1. Study Protocol

We conducted a controlled user study involving 18 volunteer annotators affiliated with a university institution. All participants completed a mandatory training session based on a standardized annotation guide to ensure consistent behavior. The protocol defined a dual-objective task: users

were required to segment all distinct content within the footage—grouping frames that shared the same action, event type, or scenario—and then classify each segment. To reduce ambiguity, the guide explicitly defined ‘abnormal events’ as any ‘criminal, accidental, or catastrophic’ incident, with all other content defaulting to ‘normal’.

To control for attentional bias, the protocol mandated that annotators view each video in its entirety before beginning segmentation. Participants were instructed that frame-perfect precision was not the primary objective, with a target task duration of 8-12 minutes per video to simulate realistic, labeling conditions.

For evaluation, we randomly sampled 30 videos from the datasets (Section 4.1) test sets. The study utilized a counterbalanced A/B design. Each participant annotated a unique batch of 10 videos: 5 in the Assisted Condition (with generated Pre-Annotations) and 5 in the Unassisted Condition (raw footage). The order of conditions was randomized to decouple the tool’s “learning curve” from the impact of the suggestions, half the cohort began with Condition A and the other half with Condition B. The average session duration was approximately 60 minutes.

Given the inherent subjectivity of defining anomaly boundaries in untrimmed video, we did not rely on a single ground truth. Instead, we employed a 6-vote overlap crowdsourcing strategy. Each video in the test subset was annotated by six independent participants (three using the assisted workflow, three unassisted). This aggregation allows us to construct a Consensus Ground Truth by identifying the temporal segments where the majority of annotators agreed, filtering out individual noise and capturing the “natural” semantic boundaries of the events.

For full transparency regarding annotator recruitment, compensation, and ethical considerations, we have included a complete CrowdWorkSheets response in Appendix B. This documentation framework is widely employed in similar human-centric AI studies to ensure reproducibility and ethical rigor (Gustafson et al., 2023).

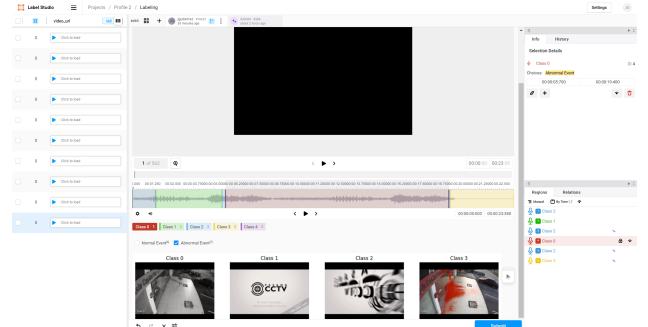
To manage the annotation task and compute pre-annotations, we deployed a hybrid workflow that integrates an adapted version of an open-source annotation tool with a resource-efficient cross-modal encoding pipeline. We utilize a proven retrieval framework—characterized by fine-tuned encoders and hierarchical clustering—as a controlled variable. This ensures that pre-annotations are grounded in a consistent semantic structure, allowing us to isolate and quantify the specific impact of algorithmic suggestion on human efficiency. The human interface had to be adapted for this specific task.

3.2. Providing a Graphical User Interface

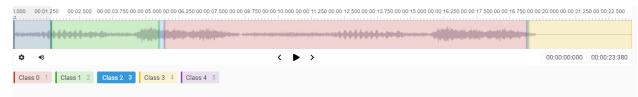
We integrated our Pre-Annotation pipeline with Label Studio, an open-source data labeling platform selected for its flexibility and robust feature set (Tkachenko et al., 2020). The interface was customized to support a dense temporal annotation task where users categorize video segments into distinct classes. To facilitate reproducibility, the exact Label Studio interface configuration and template code are released alongside the project repository.

As illustrated in Figure 1, the interface comprises two primary components: a video rendering module for content inspection and a temporal control layer. This layer features two synchronized timelines: a video navigation bar and an annotation bar where segments are actively manipulated. The interface also includes playback speed controls to facilitate rapid scanning. Additionally, the interface includes controls for binary classification, enabling annotators to explicitly flag segments containing specific events (e.g., abnormal vs. normal activities).

In the assisted workflow, the Pre-Annotation pipeline populates this timeline with suggested segments—the “strong clusters” derived from the Pre-Annotation pipeline—before the user begins. The annotator’s task effectively shifts from creating annotations from scratch to a verification and refinement process. Users must explicitly duplicate the read-only predictions into their active workspace, where they can adjust boundaries and correct class labels. To expedite this process, the interface supports keyboard shortcuts (e.g., Ctrl+C/V) for replicating segments. To further support this



(a) The main annotation workspace featuring the video player and class taxonomy controls.



(b) Detail of the temporal timeline showing pre-populated segments and binary selection toggles.

Figure 1. The customized Label Studio interface adapted for the hybrid workflow. Users interact with generated Pre-Annotations directly on the temporal bar (b), refining the suggested segments.

decision-making, the system provides keyframes—closest frame to the cluster center—representing each class as visual references during the process.

3.3. Producing the Pre-Annotations

We employ a cross-modal retrieval architecture explicitly adapted for video downstream tasks (Radford et al., 2021) to generate high-quality suggestions for the HITL workflow. This pipeline serves as the generator of “strong clusters”—semantically coherent video segments that are presented to annotators for verification.

We explicitly leverage a frame-video dataset approach, as it allows for the robust maintenance of semantic information while incorporating spatiotemporal cues without prohibitive computational costs. This resource-efficient strategy has been validated in prior works (Rasheed et al., 2023; Ma et al., 2022b; Luo et al., 2021).

Encoding and Training Procedure Given a set of video-text pairs (V, P) , we treat each video clip $V_i \in \mathbb{R}^{N \times H \times W \times C}$ as a sequence of N frames. To capture temporal consistency without overhead, we employ a temporal pooling strategy. Each frame in V_i is encoded to yield frame-level features $z_i \in \mathbb{R}^{N \times D}$. We then obtain a video-level embedding $v_i \in \mathbb{R}^D$ by applying average pooling over the N frames, aggregating temporal data into a single fixed-size representation (Rasheed et al., 2023).

In parallel, the corresponding text description p_i is processed by the text encoder to produce an embedding $t_i \in \mathbb{R}^D$ in the shared feature space. The alignment between modalities is driven by the cosine similarity $\text{sim}(v_i, t_i)$. We fine-tune the encoders using a contrastive approach, optimizing the symmetric Cross-Entropy (CE) loss. For a batch size of N , the loss for video-to-text is defined as:

$$\mathcal{L}_{v2t} = -\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(\text{sim}(v_i, t_i)/\tau)}{\sum_{j=1}^N \exp(\text{sim}(v_i, t_j)/\tau)} \quad (1)$$

To ensure the model is robust for both retrieval directions, we apply a Multi-Task Learning (MTL) objective. The total loss $\mathcal{L}_{\text{total}}$ averages the losses for both video-to-text and text-to-video directions:

$$\mathcal{L}_{\text{total}} = \frac{1}{2} (\mathcal{L}_{v2t} + \mathcal{L}_{t2v}). \quad (2)$$

Figure 2 illustrates our proposed approach. This optimization ensures that the embedding space maximizes the similarity between correct video-text pairs while minimizing it for incorrect ones (Dong et al., 2021). By training on video clips paired with detailed textual descriptions, the model learns to effectively address zero-shot and open-class scenarios. We further analyze the effectiveness of this training in Appendix A.3.

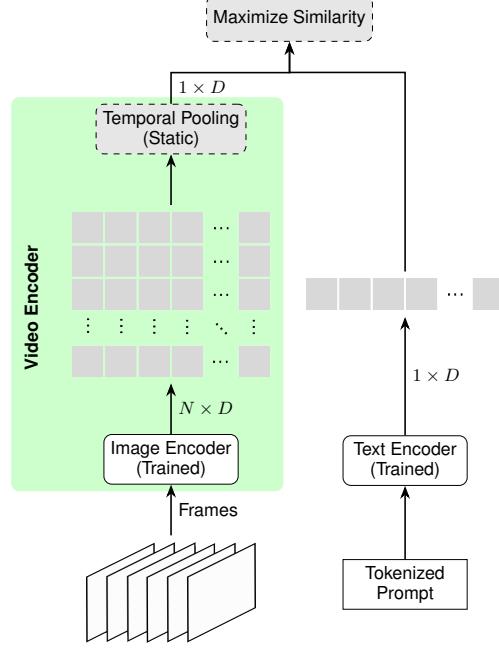


Figure 2. Architecture of the Pre-Annotation pipeline. Video frames are processed by the image encoder to generate frame-level embeddings, which are pooled to produce a video-level embedding. These are aligned with text embeddings via contrastive learning, creating the semantic foundation for the hierarchical clustering.

Hierarchical Content Modeling To produce the actual Pre-Annotation segments, we model the video feature space as a hierarchical tree depicted in Figure 3. This structure reflects the inherent granularity of video content, from broad environments to specific actions.

We construct this tree by recursively clustering the feature arrays using spherical k -means (Hornik et al., 2012). This variant maximizes cosine similarity between data points and centroids, aligning with the n -dimensional hyperspherical nature of the CLIP latent space (Liang et al., 2022). The objective function is defined as:

$$\max_{r_{ij}, \mu_j} \sum_{i=1}^p \sum_{j=1}^k r_{ij} \frac{\mu_j \cdot \mathbf{x}_i}{\|\mu_j\| \|\mathbf{x}_i\|} \quad (3)$$

subject to $r_{ij} \in \{0, 1\}$ and $\sum_{j=1}^k r_{ij} = 1$ for all i , where μ_j is the centroid of cluster j , \mathbf{x}_i is the i -th data point, and $r_{ij} = 1$ if and only if \mathbf{x}_i is assigned to cluster j . The process begins with high-level clusters, and progressively refines them into fine-grained nodes until a stopping criterion is met. To ensure the segments represent meaningful semantic units rather than arbitrary temporal splits, we employ a maximum tree depth constraint (set to $T_{\max}=3$) and a semantic cohesion threshold, halting the recursive subdivision when the cosine similarity within a cluster exceeds $\tau = 0.85$. The resulting leaf nodes represent “strong clusters” that we interpret as distinct video segments. These segments constitute

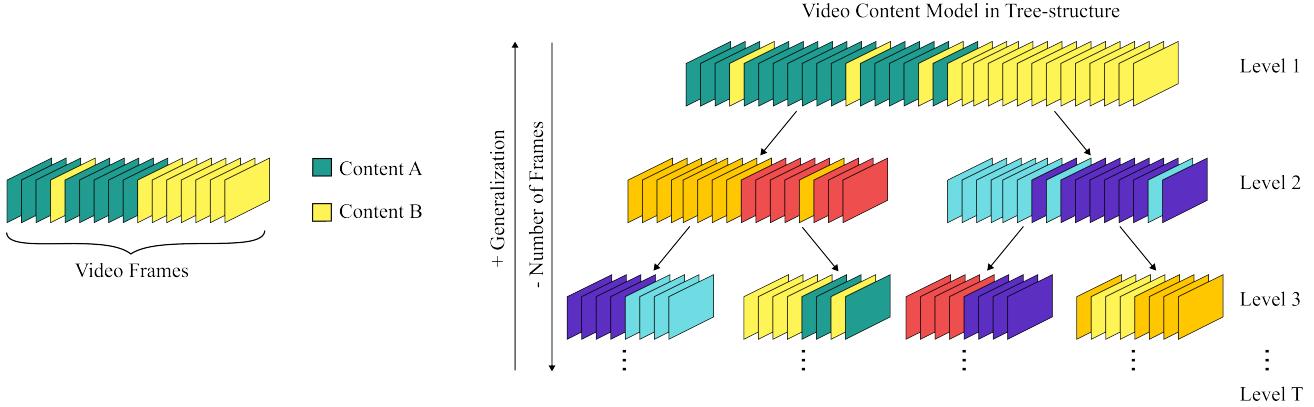


Figure 3. Hierarchical clustering of video content. Frames (left) are recursively clustered into a tree structure (right) using spherical k -means. This structure allows the Pre-Annotation pipeline to propose segments at different levels of granularity, which users then verify or refine.

the Pre-Annotations provided to the human annotators and serve as the starting point for our evaluation.

4. Evaluation & Analysis

To provide a complete assessment of the hybrid workflow, we evaluate the results across three distinct dimensions: Efficiency (temporal gains), Consistency (inter-annotator agreement), and Standardization (structural coherence). Figure 4 outlines the evaluation framework, illustrating how raw logs, class labels, and frame embeddings are processed to derive these metrics.

4.1. Training Datasets & Setup

Datasets. We utilized a diverse composite of four datasets to ensure the encoder’s robustness across varying temporal structures and semantic contexts. UCF-Crime (Sultani et al., 2018) serves as the foundational domain, providing 1,900 untrimmed real-world surveillance videos (128 hours) characterized by low resolution and unconstrained viewpoints. To enable fine-grained semantic alignment, we incorporated UCA (Wu et al., 2024), which enhances UCF-Crime with 23,542 linguistic annotations spanning 110.7 hours of the original footage. We further expanded the training distribution with XD-Violence (Wu et al., 2020), contributing 4,754 untrimmed videos totaling 217 hours, and ActivityNet Captions (Krishna et al., 2017), which adds 849 hours of footage across 20,000 videos. This diverse training corpus ensures the model is exposed to a wide spectrum of visual environments, action durations, and linguistic complexities.

Training Setup. The cross-modal encoder was fine-tuned on an NVIDIA A100 GPU (40 GB VRAM). We implemented a cosine learning rate decay policy (Loshchilov & Hutter, 2017b), which gradually reduces the learning rate to optimize convergence. The initial learning rate (lr_{base})

was set to 8×10^{-6} , selected based on successful configurations in similar CLIP fine-tuning tasks (Rasheed et al., 2023; Ma et al., 2022b). We employed the AdamW optimizer (Loshchilov & Hutter, 2017a) with a decoupled weight decay parameter of 1×10^{-3} . The learning rate optimization follows the cosine annealing schedule defined as:

$$lr(t) = \frac{1}{2} lr_{\text{base}} \left(1 + \cos\left(\frac{t - t_{\text{warm-up}}}{T_{\text{total}} - t_{\text{warm-up}}} \pi\right) \right) \quad (4)$$

where T_{total} represents the total number of training steps and $t_{\text{warm-up}}$ denotes the number of warm-up steps. Given that model performance is highly sensitive to input granularity and batch composition, we evaluated multiple configurations during training, utilizing batch sizes ranging from 5 to 100 and frame sampling intervals of 5 to 40 equidistant frames per video clip.

4.2. Annotations and Interaction Traces

We provide the dataset containing the anonymized interaction traces from human annotators collected during our study of AI-assisted dense temporal video annotation. The dataset captures not only the final human segmentations, but also the full edit lifecycle, including model pre-annotations, the annotation guide, editing actions, and session-level timing information. This resource and the code of the adapted user interface are intended to support reproducible benchmarking of Human-in-the-Loop workflows in video annotation, enabling analyses of efficiency, revision behavior, and potential anchoring effects beyond what can be inferred from final labels alone. Table 1 provides a statistical summary of the collected data.

4.3. Temporal Analysis: Efficiency Gains

The primary objective of the hybrid workflow is to reduce the cognitive load and manual effort required for dense video

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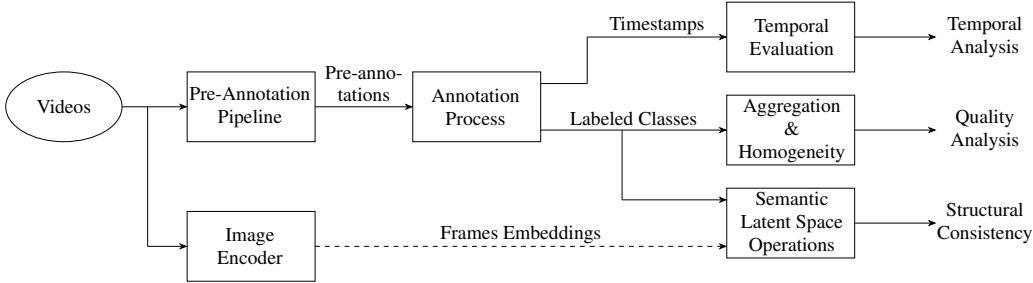


Figure 4. Evaluation framework. The diagram maps the flow from the Pre-Annotation Pipeline (black blocks) to the three pillars of analysis: Temporal Efficiency, Homogeneity, and Structural Consistency.

Table 1. Detailed statistics of the annotation dataset and interaction traces.

Metric	Value
<i>Annotation & Segments</i>	
Total Annotators	18
Total Annotation Sessions	180
Total Labeled Segments	699
<i>Semantics</i>	
Mean Classes per Video	3.01 ± 0.95
Abnormal Event Segments	323 (48.2%)
Normal Event Segments	347

labeling. We tracked the precise task duration—from initial load to submission—for all 180 annotation sessions and analyzed the time-on-task distribution (Figure 5), which follows a Gamma-like distribution characteristic of cognitive tasks (Luce, 1991). Statistical tests, detailed in Table 2, confirm the independence of the two distributions ($p < 0.005$).

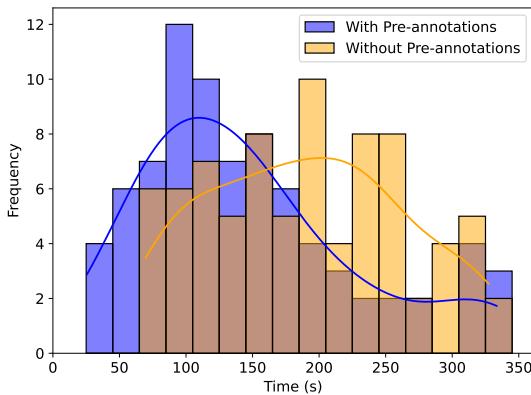


Figure 5. Distribution of annotation times with and without Pre-Annotations. We used bin steps of 20 seconds. The kernel density plot illustrates the trend for both distributions.

As shown in Table 3, the results indicate a mean time reduction of 23.11% across the cohort. However, when normalizing for individual annotator speed, we observe that 72% of

Table 2. Statistical comparison of annotation times between assisted and unassisted workflows. Both parametric (t -test) and non-parametric (Wilcoxon) tests confirm a statistically significant difference between the distributions ($p < 0.005$).

TEST	STATISTIC	p-VALUE
t -TEST	-3.64	0.0004
WILCOXON	853.0	0.0002

Table 3. Descriptive statistics for annotation time (in seconds).

CONDITION	MEAN	STD
ASSISTED	146.42	79.28
UNASSISTED	190.44	72.63

participants worked faster with the automatic suggestions, achieving a median improvement of 35%. Figures 7a–b break this down per anonymized user; points above the green area indicate efficiency gains. Notably, we found no correlation between the time savings and the video duration or class count (Figure 6), suggesting the efficiency gain is robust to varying content complexity.

A temporal analysis of the user sessions (Figures 7c–d) reveals that the benefit of Pre-Annotation increased over time. By excluding the first four “training” videos, the efficiency gap widens, indicating that as users become familiar with the tool, they become more adept at verifying suggestions rather than re-doing them.

Annotator feedback suggests that the complexity of video annotation plays a significant role in annotation time, involving separable actions, content comprehension, and video quality. Although challenging to quantify, annotators have concurred that Pre-Annotation significantly reduces decision-making time regarding class distribution. Multiple cases of “perfect” Pre-Annotation were reported, where annotators only needed to review and submit the pre-annotated results, resulting in maximum time savings. Hence, analyzing raw data trends, most annotators experienced reduced annotation time, indicating tangible efficiency gains.

4.4. Quality Analysis: Convergence and Inter-Annotator Stability

Defining the exact temporal boundaries of anomalous events involves inherent subjectivity. Rather than enforcing rigid, artificial constraints, we evaluate how the workflow manages this natural ambiguity through two dimensions: alignment with a consensus baseline (Accuracy) and agreement among annotators (Homogeneity).

We establish a Consensus Baseline by aggregating the classifications of all six annotators per video. By grouping identical frame-level label permutations, we isolate the “strong clusters” where the majority of users agree, filtering out individual noise. We then quantify performance using Adjusted Mutual Information (AMI). An AMI of 1.0 indicates perfect alignment, while 0.0 implies random correlation.

Table 4 presents the comparative analysis. To address concerns that assistance might induce blind acceptance, a passive anchoring bias in which users accept incorrect suggestions, we examine the alignment of individual sessions against the Consensus Baseline. If the Pre-Annotations introduce systematic biases or if users were passively accepting hallucinated labels, we would expect a degradation in alignment with this baseline. However, both the assisted and unassisted groups maintain a nearly identical

Table 4. Comparative analysis of annotation metrics. We evaluate two dimensions: alignment with the Consensus Baseline (Accuracy) and Inter-Annotator Consistency (Homogeneity). Abbreviations: Adjusted Mutual Information (AMI), Normalized Mutual Information (NMI), and V-measure (V).

CONDITION	AMI	NMI	V
<i>Consensus Alignment (Accuracy)</i>			
ASSISTED	0.64	0.64	0.64
UNASSISTED	0.63	0.64	0.64
<i>Inter-Annotator Consistency</i>			
ASSISTED	0.67	0.67	0.67
UNASSISTED	0.62	0.62	0.62

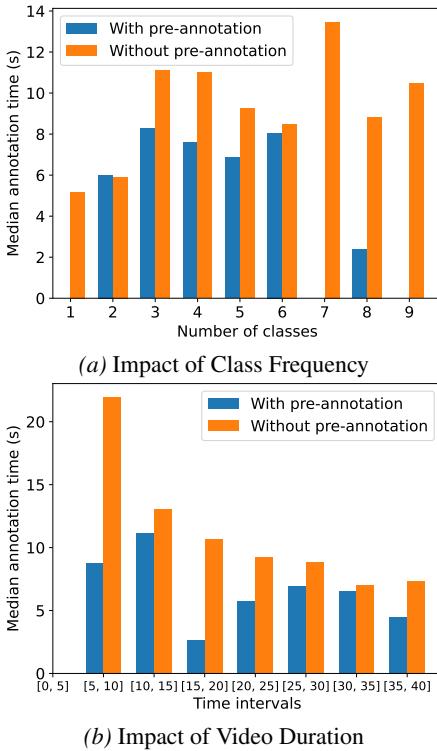


Figure 6. Efficiency gains against content complexity. The plots display median annotation times stratified by (a) non-unique classes per video and (b) video duration (5-second bins).

alignment score ($\text{AMI} \approx 0.64$). This parity indicates that Pre-Annotation suggestions do not distort user judgment or induce deviation from collective semantic consensus. Instead, users actively verify and correct automatic suggestions, preserving alignment with the natural group wisdom observed in the unassisted condition.

We evaluated Inter-Annotator Consistency (Homogeneity). Here, a significant divergence appears (Table 4, down rows). The assisted group demonstrated notably higher agreement with each other (AMI: 0.67) compared to the unassisted group (AMI: 0.62).

In the absence of strict definitions, unassisted annotators exhibited high variance in boundary selection (“jitter”). The Pre-Annotation workflow mitigated this not by enforcing an arbitrary correct answer (which would lower the consensus score), but by providing a “semantic anchor.” This proves that the workflow successfully acts as a standardization mechanism, reducing the stochastic noise inherent to human labeling without altering the fundamental semantic classification of the events.

4.5. Semantic Standardization: Latent Space Analysis

We evaluate the structural coherence of the annotations using latent-space analysis. We compute the Silhouette Score of the annotated segments using the CLIP image encoder (Radford et al., 2021) and cosine distance. While evaluating with the same encoder family used for generation introduces inductive bias, we employ this metric specifically to quantify standardization, not for ground truth validation. In high-ambiguity domains, unassisted human annotation is prone to significant stochastic variance (semantic jitter); we hypothesize that the assisted workflow acts as a regularizer.

We adopt the Silhouette Score—typically used for generative fidelity (Zheng et al., 2023; Tao et al., 2023)—as a proxy for internal consistency (Shahapure & Nicholas, 2020). As illustrated in Figure 8, the assisted workflow improved structural coherence in 25 of 30 videos. The mean Silhouette

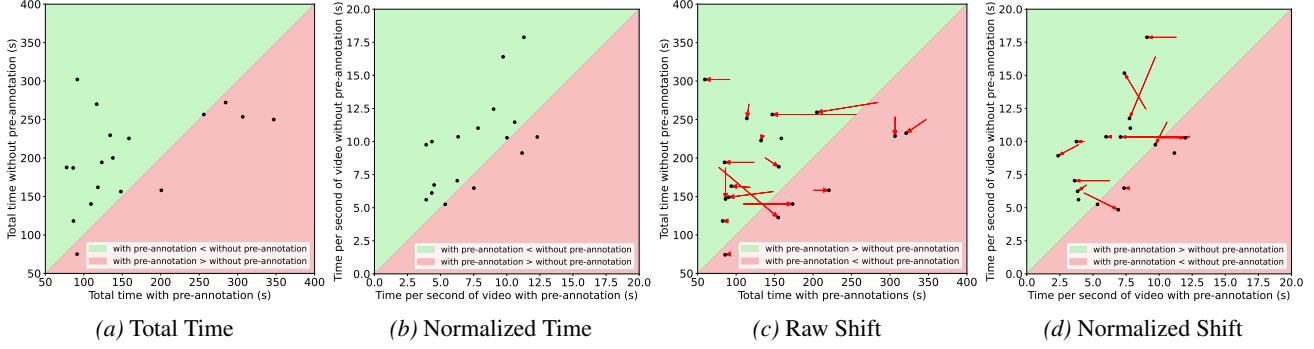


Figure 7. Per-user efficiency analysis. (a–b) Total and normalized annotation time per user; points in the green zone indicate users who were faster with Pre-Annotation assistance (72% of participants). (c–d) Changes in efficiency after excluding the first four training videos; each red arrow represents the change for an annotator.

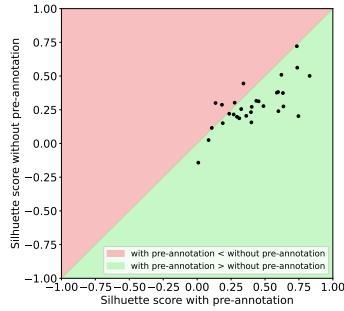


Figure 8. Latent Space Standardization. Each point represents a video. Points in the green region denote videos where the assisted workflow yielded higher Silhouette Scores, indicating a reduction in stochastic annotator variance (jitter) relative to the unassisted baseline.

Score increased from 0.28 (unassisted) to 0.41 (assisted), a relative improvement of 52.10%.

Crucially, this increased standardization does not degrade semantic accuracy. As reported in Table 4, the assisted cohort maintained a Consensus Alignment (AMI) of 0.64, equivalent to the unassisted baseline. Consequently, the increase in Silhouette Score indicates that the Pre-Annotation pipeline successfully filters out inter-annotator noise without distorting the underlying semantic consensus.

5. Conclusions

In this work, we introduced a Human-in-the-Loop (HITL) workflow for dense temporal video segmentation that reduces the cost of producing high-quality labels by reframing annotation as verification-and-editing rather than from-scratch creation. We move beyond simulated studies and evaluate the workflow in a controlled experiment with 18 annotators labeling open-world footage, allowing us to measure how AI assistance changes the annotation process in practice.

Our results show that model-generated Pre-Annotations substantially improve efficiency: annotation time decreases by a median of 35% for most participants. Importantly, these gains are not achieved simply by making annotators agree more at the expense of meaning. Instead, the resulting segmentations exhibit greater structural standardization and greater cross-annotator homogeneity, consistent with algorithmic guidance that helps annotators converge on clearer temporal boundaries rather than introducing semantic drift.

To support reproducibility and enable follow-up work on human–model interaction dynamics, we release the full open-source implementation of the pipeline, the analysis code, and an anonymized dataset of interaction traces. Together, these artifacts provide a validated methodology for studying and benchmarking AI-assisted annotation and offer a practical foundation for scaling the creation of complex, densely labeled video datasets.

Impact Statement

This work advances data-centric AI by improving Human-in-the-Loop workflows for dense temporal video segmentation, reducing the cost and effort required to build high-quality datasets for video understanding and anomaly detection. By shifting the role of the annotator from creating labels from scratch to reviewing and correcting model-generated Pre-Annotations, the workflow can increase efficiency; but it also changes the human–AI interaction in ways that matter for data quality. In particular, Pre-Annotations can introduce anchoring bias, leading annotators to unintentionally be steered toward the model’s proposed boundaries or categories. Effective systems must therefore be designed to preserve human agency and encourage active verification rather than passive acceptance of algorithmic outputs.

Finally, these workflows are often used on open-world footage that may include sensitive, explicit, or distressing content. Researchers and practitioners should apply rigor-

ous ethics and safety practices—such as content warnings, opt-out mechanisms, and appropriate support—to protect the psychological well-being of annotators.

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A. Video Encoder Evaluation

In this appendix, we provide a detailed evaluation of the cross-modal video encoder used in our Pre-Annotation Pipeline. While the main body of this paper focuses on the human-centric evaluation of the workflow, verifying the robustness of the underlying model is essential to validate the quality of the suggestions provided to the annotators.

A.1. Evaluation Protocols

Video-Text Matching. We evaluated the cross-modal encoder’s ability to pair videos with corresponding text snippets accurately. The model predicts the most probable (video, text) pairs based on embeddings generated by the encoders. These embeddings, representing the semantic essence of both modalities, are compared using cosine similarity, scaled by a temperature parameter, and normalized via softmax to produce a probabilistic prediction of the correct pairing.

The model was trained for 30 epochs, balancing time and learning performance, with monitoring to select the best-performing epoch for final evaluation. All videos were divided and matched with the corresponding descriptions provided in the UCA dataset. During the accuracy calculation, we introduced randomness by selecting video-clips from within the same video and across different videos.

Metrics. We used two different metrics for evaluation. During training, we assessed the model’s ability to associate video-clips with the corresponding text using Accuracy at Rank K (Acc@ K , where higher is better). Acc@ K represents the percentage of test samples for which the correct result is found within the top- K retrieved video-clips corresponding to the query sample. We report on Acc@1 and Acc@5.

A.2. Quantitative Results and Ablation

Training Results. Table 5 reveals that the ViT-B/16 architecture with a batch size of 10 and 16 sampled frames achieved the highest top-1 accuracy of 89.68% and a top-5 accuracy of 99.64%. Other configurations, such as the ViT-B/32 with varying batch sizes and sampled frames, also demonstrated competitive performance, though with some variation in accuracy depending on the specific setup.

Effect of Frame Sampling. Frame sampling is critical in determining the balance between computational efficiency and retrieval accuracy. We reduce the computational load by selecting a subset of frames rather than processing the entire video. However, with scarce sampling frames, one may omit important temporal or semantic cues, degrading the model’s performance.

We experimented with different sampling intervals to evaluate the effect of frame sampling, as shown in Table 5. When sampling fewer frames (for example, 5 or 16 frames), the retrieval accuracy improves significantly, with Acc@1 reaching 89.68% for ViT-B/16 with 16 sampled frames. Sampling 30 frames with ViT-B/16 slightly decreases the Acc@1 score to 73.59%, indicating a diminishing return when too many frames are processed simultaneously. This suggests that there is an optimal range of frame sampling that balances both efficiency and performance. Sampling too few frames may hinder accuracy while sampling too many frames may introduce unnecessary redundancy and increase computational complexity.

Impact of Model Backbone. The model architecture, particularly the backbone choice, is crucial in retrieval performance. We compared two versions of the CLIP architecture: ViT-B/16 and ViT-B/32. Table 5 details that the ViT-B/16 backbone consistently outperforms ViT-B/32 in accuracy. For example, with a batch size of 10 and 16 sampled frames, ViT-B/16 achieves 89.68% Acc@1 and 99.64% Acc@5, significantly outperforming ViT-B/32, which achieves Acc@1 scores of around 73%.

The improved performance of ViT-B/16 is likely due to its ability to capture more detailed spatiotemporal relationships, thanks to its higher-resolution feature representations. While ViT-B/32 provides competitive results and is less computationally expensive, the added granularity of ViT-B/16 proves more beneficial for tasks requiring precise retrieval across long and complex video sequences.

A.3. Attention Shift

To understand how the fine-tuned encoder processes temporal dynamics, we analyzed the self-attention maps of the Vision Transformer (ViT) (Vaswani et al., 2017; Radford et al., 2021). Rather than treating the model as a black box, we visualized the attention weights to verify that the model focuses on relevant spatiotemporal actions.

Table 5. Performance comparison of various CLIP fine-tuning configurations. The table shows results for different backbone architectures (ViT-B/16 and ViT-B/32), batch sizes, and numbers of sampled frames. Performance metrics are evaluated using Acc@1 and Acc@5.

BACKBONE	BATCH SIZE	SAMPLED FRAMES	ACC@1 (%)	ACC@5 (%)
RANDOM	-	-	8.17	39.89
ViT-B/16	10	16	89.68	99.64
	30	30	73.59	95.30
ViT-B/32	5	30	73.71	95.20
	30	5	73.71	95.20
	20	32	81.76	97.75
	100	40	59.59	86.24

Methodology. We extracted the self-attention weights from the multi-head attention layers of the ViT. Specifically, we computed the cumulative joint attention across layers and isolated the attention maps associated with the class (CLS) token. Since the CLS token serves as the global aggregate representation of the sequence, its attention map reveals which spatial patches the model deems most significant for the final classification. We averaged these weights across heads and upscaled them to match the input frame resolution for visualization (Li et al., 2023; Ma et al., 2022a).

Visual Analysis. Visualizing attention maps across various layers of the fine-tuned Vision Transformer (ViT) reveals essential insights into the model’s interpretation and processing of video data. Figure 9 illustrates the model’s ability to focus on relevant spatial and temporal aspects within input sequences, reflecting an enhanced understanding of inter-object relationships and scene dynamics.

The analysis of these attention maps reveals several key insights. In the “Vandalism034” video-record, the model effectively tracks the aggressive interactions between individuals and the trash can, highlighting the critical movements that define the event. Similarly, in the “Stealing004” case, the model accurately identifies the coordinated actions of the individuals involved in the theft, with a strong focus on the movement of the motorcycle and the interactions surrounding it. These examples showcase the model’s capability to discern complex, temporally extended activities.

In the “Normal_Videos_352” video-record, which depicts routine activities like refueling cars, the attention maps demonstrate the model’s ability to recognize and focus on key actions, such as the departure of the car and the movements of individuals at the gas station. This indicates that the model can distinguish routine behaviors from more significant or unusual ones. In the “Abuse005” video-record, involving a prison guard’s interactions, the model focuses on the guard’s movements and posture, reflecting an understanding of the scene’s context and the key actions that convey the narrative.

These findings underscore the model’s inherent ability of the proposed encoder to learn and generalize temporal relationships through fine-tuning on video datasets, even without explicit temporal modeling modifications. The attention mechanisms allow the ViT to prioritize important features and actions, leading to enhanced performance in video understanding tasks.

B. Experimental evaluation CrowdWorkSheets

To further describe our annotation process, we include our responses to the CrowdWorkSheets questionnaire (Díaz et al., 2022). CrowdWorkSheets is a framework for transparent and ethical dataset annotation that emphasizes the annotation process’s documentation, considering the annotators’ identities and experiences. The framework provides guidance on ethical considerations, annotator selection, and documentation of the annotation process, aiming to address unresolved ethical issues in crowdsourcing. More importantly, it allows us to share a complete summary of the annotation process conducted to ease replicating the test and to highlight the key aspects behind its execution.

B.1. Task Formulation

At a high level, what are the subjective aspects of your task?

This annotation test is highly subjective in various aspects. The annotator can decide on the criteria for grouping the frames. This decision has been made intentionally in the test’s design, as it aims to contrast with the classification criteria of our pipeline using CLIP. Determining what constitutes an “anomalous” or “normal” event is quite ambiguous, even for individuals. The most effective way to achieve a valid evaluation is through consensus among multiple annotations.

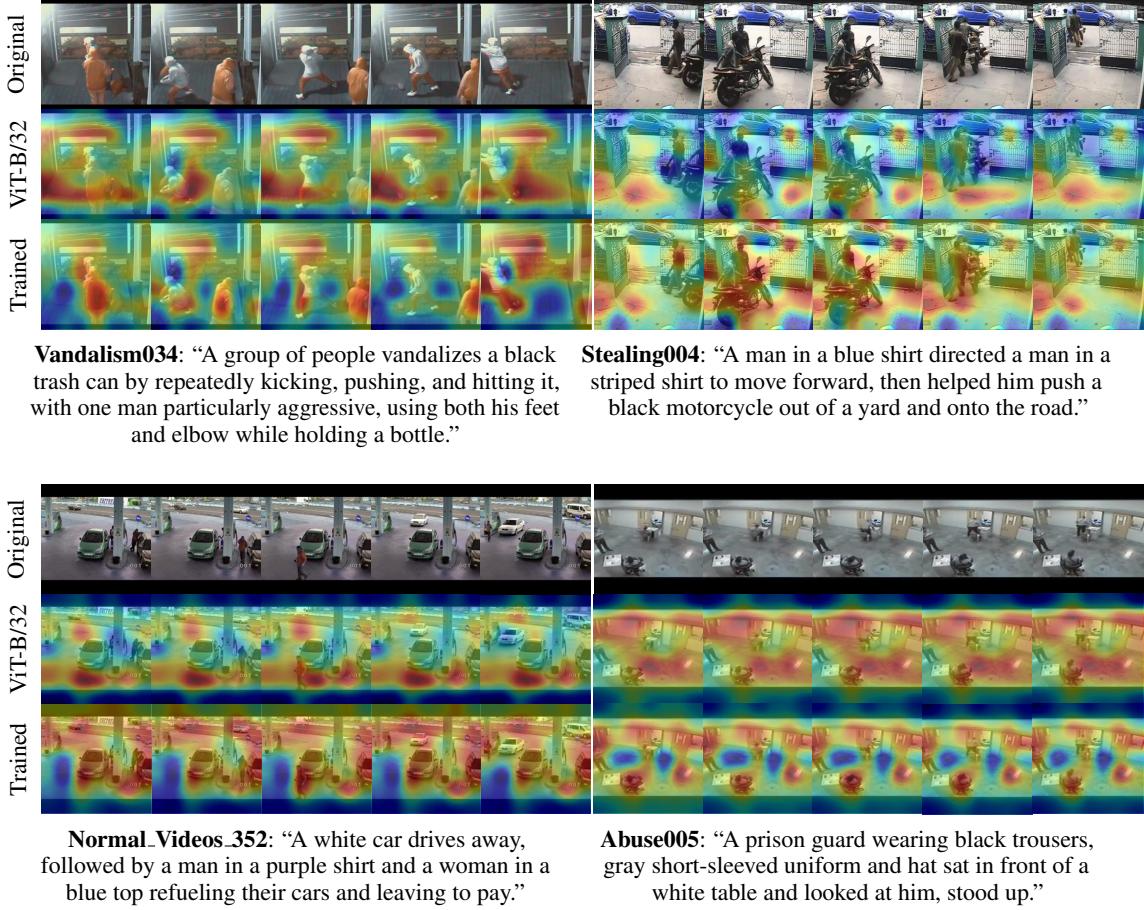


Figure 9. Visualization of attention maps on UCF-Crime. Each merged image contains three stacked rows (Original, ViT-B/32, Trained) and two video samples per row (left / right). Rotated labels are placed at the centers of the three thirds of the merged image height; descriptions are side-by-side beneath each merged image.

Another significant point of subjectivity is the delineation between events. Sometimes, the boundary between the end of one event and the beginning of the next, or even whether they can be considered separate events, is very subtle. To minimize the bias of each annotator and select the most “valid” annotation, we have employed a method that involves obtaining three annotations for each type from each video. Consequently, we gathered six annotations for each video, providing greater confidence in the evaluation.

What assumptions do you make about annotators?

Some of the key assumptions we made about our annotators are as follows:

- Providing the context of the test and explaining the objectives of this work, where disagreements are expected, is intended to enhance each annotator’s criteria to achieve diverse results.
- We assume that the annotators are committed to conducting the test accurately. This assumption is based on their status as trusted individuals within a university department and their academic interest in the test, given their involvement in projects of the same theme.
- It is assumed that all annotators possess their own personal criteria for evaluating what is considered anomalous, acquired through lived experiences.

How did you choose the specific wording of your task instructions? What steps, if any, were taken to verify the clarity of task instructions and wording for annotators?

To delineate the task without overly restricting the annotator’s freedom of judgment, a somewhat broad definition of

anomalous events has been provided: criminal, accidental, or catastrophic events. The instructions have been validated multiple times by different researchers, incorporating modifications.

To help the understanding of any annotator, instructions start from the lowest possible level, using standard, concise, and precise vocabulary. Additionally, the test was deployed in groups, beginning with the most confident annotators, and the annotation guide was updated after each batch.

Any annotator who requested it has received direct support to clarify any doubts that may have arisen during the process. This approach ensures a clear and consistent framework for the annotation task.

What, if any, risks did your task pose for annotators, and were they informed of the risks prior to engagement with the task?

Our task involves annotators reviewing videos that potentially contain violent, explicit, catastrophic, and other types of harmful content. Consequently, the task carries a risk of psychological harm to annotators. Additionally, we have deliberately selected annotators who share cultural similarities with the researchers to ensure that, after filtering the videos, the criteria for identifying images considered too intense for annotators are aligned. Therefore, annotators from significantly different nationalities and cultures from the Spanish context were excluded.

Before commencing the task, each annotator was informed of the video content to be encountered, ensuring they were adequately prepared and provided their consent. Furthermore, the videos underwent an additional review by different researchers, allowing each to exercise discretion in excluding content deemed excessively intense for the annotator.

What are the precise instructions that were provided to annotators?

Annotators will be tasked with annotating open-world videos. The estimated duration of the test is less than 30 minutes, with 2-4 minutes allocated for each video. Prior filtering has been conducted to exclude videos containing overly sensitive imagery.

Each annotator is required to annotate 10 videos, with 5 left without Pre-Annotation and 5 pre-annotated automatically. In the case of pre-annotated videos, annotators are instructed to review the annotations and make necessary modifications.

Annotation involves grouping frames with similar content by marking them on a temporal bar and assigning a class to each segment. The criteria for considering content as similar include the occurrence of the same action, any event, or a similar setting. Additionally, each segment should be classified as either a “normal event” or an “abnormal event”, the latter being defined when a criminal, accidental, or catastrophic event occurs.

Each annotator has been assigned a profile within the annotation tool, specifying the order in which the assigned videos should be annotated. We provided the annotators with a guide for using the annotation tool interface has been provided, along with tips on navigating the selection bar, using commands, and assigning classes.

It is recommended that annotators practice with a sample video before becoming familiar with the tool. Additionally, annotators are advised to view the entire video before annotation to grasp the context of all events occurring globally in the video.

B.2. Selecting Annotators

Are there certain perspectives that should be privileged? If so, how did you seek these perspectives out?

No. N/A

Are there certain perspectives that would be harmful to include? If so, how did you screen these perspectives out?

No. N/A

Were sociodemographic characteristics used to select annotators for your task?

The annotators are all volunteers who chose to participate in the task. They are exclusively Spanish individuals with a minimum academic background of university education. None of the annotators have prior experience in annotation tasks, and they are all affiliated with a university. The annotator pool is well-balanced in terms of gender, and the age range spans from 18 to 50.

If so, please detail the process. If you have any aggregated sociodemographic statistics about your annotator pool, please describe.

Other sociodemographic statistics about our annotator pool were not available.

Do you have reason to believe that sociodemographic characteristics of annotators may have impacted how they annotated the data? Why or why not?

It is possible that, being a somewhat homogeneous group, annotators may share a similar perception of what is considered normal or abnormal in the videos.

Consider the intended context of use of the dataset and the individuals and communities that may be impacted by a model trained on this dataset. Are these communities represented in your annotator pool?

The purpose of this test is solely to evaluate our Pre-Annotation pipeline. Although the potential bias introduced into the data by Pre-Annotations is studied in Section 4.

B.3. Platform and Infrastructure Choices

What annotation platform did you utilize?

We used Label Studio ([Tkachenko et al., 2020](#)) for our annotation needs.

At a high level, what considerations informed your decision to choose this platform?

We opted for Label Studio for several reasons: Firstly, it is a generally reliable platform with a track record in annotating high-quality data. It is free and open-source, providing extensive customization options for the annotation interface. Additionally, it offers essential functionalities for our test, such as frame classification over a temporal bar and automatic, precise measurement of annotation time per video.

Did the chosen platform sufficiently meet the requirements you outlined for annotator pools? Are any aspects not covered?

The selected platform adequately covered all the needs of this experiment.

What, if any, communication channels did your chosen platform offer to facilitate communication with annotators?

How did this channel of communication influence the annotation process and/or resulting annotations?

Both direct interaction and an external medium, email, were utilized for communication. Technical queries regarding the tool were addressed directly. In uncertainty related to the annotation process, annotators were informed of the freedom of interpretation, emphasizing that no criterion is more valid than another to avoid influencing annotations.

How much were annotators compensated? Did you consider any particular pay standards, when determining their compensation? If so, please describe.

No compensation was provided to any annotator; all participated voluntarily. While some may have academic interest in this study, no financial incentives were offered.

B.4. Dataset Analysis and Evaluation

How do you define the quality of annotations in your context, and how did you assess the quality in the dataset you constructed?

To ensure the precision of annotation time in a hypothetical scenario involving the annotation of large volumes of data, annotators initially practiced using a test video to familiarize themselves with the annotation tool. Outliers were eliminated if they exhibited a significant deviation from the rest of the annotations. Assessing the accuracy of annotations in this test is challenging due to the experimental nature and lack of a ground truth. In such cases, the only viable approach is to annotate the same video multiple times to determine the average consensus among annotations.

Have you conducted any analysis on disagreement patterns? If so, what analyses did you use and what were the major findings? Did you analyze potential sources of disagreement?

An extensive study on the consistency of annotations and, consequently, the patterns of disagreement has been conducted; it is detailed in Section 4.

How do the individual annotator responses relate to the final labels released in the dataset?

As mentioned earlier, the release of dataset annotations is not planned at this stage, as we are currently evaluating the annotation process. However, in a real annotation scenario, the classification of frames and keyframes would be made public, employing an agreement method among annotators' classifications. Therefore, each annotator's annotations would serve as a vote in the agreement process.