Animal-Bench: Benchmarking Multimodal Video Models for Animal-centric Video Understanding

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Abstract

With the emergence of large pre-trained multimodal video models, multiple benchmarks have been proposed to evaluate model capabilities. However, most of the benchmarks are human-centric, with evaluation data and tasks centered around human applications. Animals are an integral part of the natural world, and animal-centric video understanding is crucial for animal welfare and conservation efforts. Yet, existing benchmarks overlook evaluations focused on animals, limiting the application of the models. To address this limitation, our work established an animal-centric benchmark, namely Animal-Bench, to allow for a comprehensive evaluation of model capabilities in real-world contexts, overcoming agent-bias in previous benchmarks. Animal-Bench includes 13 tasks encompassing both common tasks shared with humans and special tasks relevant to animal conservation, spanning 7 major animal categories and 819 species, comprising a total of 41,839 data entries. To generate this benchmark, we defined a task system centered on animals and proposed an automated pipeline for animal-centric data processing. To further validate the robustness of models against real-world challenges, we utilized a video editing approach to simulate realistic scenarios like weather changes and shooting parameters due to animal movements. We evaluated 8 current multimodal video models on our benchmark and found considerable room for improvement. We hope our work provides insights for the community and opens up new avenues for research in multimodal video models. Our data and code will be released at `https://github.com/PRIS-CV/Animal-Bench`.

1 Introduction

With the rapid advancement of artificial intelligence technology, multimodal video large models [1, 2, 3, 4, 5, 6, 7, 8] have bridged the gap between video and language modalities. Leveraging extensive knowledge and powerful comprehension capabilities, these models are being applied across various areas, ushering in a new era of intelligence. The emergence of a new era of intelligence is also accompanied by the development of new evaluation benchmarks. In contrast to conventional single-task benchmarks, the new benchmarks incorporate a variety of tasks and seek to evaluate the model's intelligence across multiple dimensions. Current evaluation studies [3, 9, 10, 11, 12, 13] primarily arise from human daily needs, with a focus on human-centric application tasks, aiming to assess

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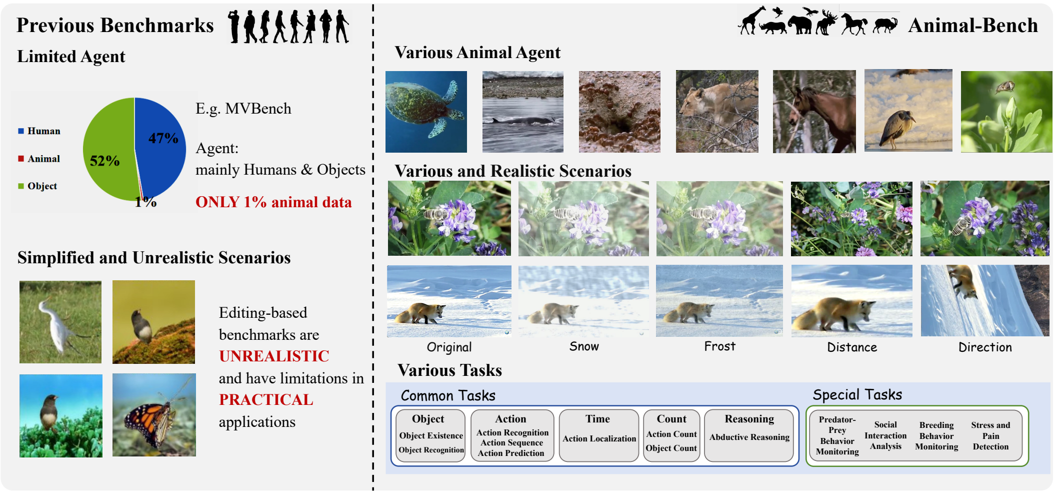

Figure 1: Previous benchmarks (left) relied on limited agent and the scenarios of editing-based benchmarks are unrealistic. Our proposed Animal-Bench (right) includes diverse animal agents, various realistic scenarios, and encompasses 13 different tasks.

model performance in common tasks encountered in human life. However, this approach confines their applicative scope to tasks centered around humans. In the broader real-world context, animals represent indispensable constituents of ecosystems [14]. They participate in vital processes such as pollination, seed dispersal, and nutrient cycling, which are essential for environmental conservation and the maintenance of biodiversity [15, 16, 17]. However, evaluations that focus on animal-centric tasks are entirely divergent from the current frameworks. As illustrated in Table 1, existing benchmarks that comprehensively evaluate model capabilities predominantly emphasize humans or objects, whereas animal-centric evaluation datasets can only assess the model's performance in few aspects. As shown in Figure 1, taking the popular benchmark MVBench [3] as an example, the main agents in the videos are humans and objects, with animal data accounting for only 1%. The inherent agent bias in these comprehensive benchmark datasets hampers our understanding of large models' ability to comprehend animal agents.

Research focusing on animal-centric evaluation overcomes the agent bias present in previous benchmarks, allowing us to assess model capabilities in a broader real-world framework, further exploring the potential applications of models and providing more valuable guidance for model optimization. The inherent diversity among animal species and the complexity of their habitats result in rich variability within animal videos, making animal-centric tasks highly challenging [18]. Evaluations on these demanding tasks can reveal the weaknesses of models in complex environments and analyze the robustness of multimodal video models against significant intra-class variations. Moreover, the applications of artificial intelligence in the field of animal studies are extensive [19, 20, 21, 22, 23, 24]. For instance, automated species counting [25, 26, 27] aids in tracking population dynamics in natural reserves, assessing overall ecosystem health, and significantly reducing human effort. Automated detection of animal stress and pain [28, 29, 30, 31, 32, 33] enables timely identification of potential issues, facilitating early treatment and ensuring animal welfare. Therefore, evaluations of models focused on animals are beneficial for further advancing the practical applications of artificial intelligence in the animal world. In summary, conducting animal-centric model evaluation plays a pivotal role in both model development and conservation efforts.

In this work, we propose Animal-Bench, a benchmark for evaluating multimodal video models in animal-centric video understanding. We choose tasks from two broad aspects: common tasks shared with human-centric benchmarks, covering aspects such as "object", "action", "time", "count", and "reasoning", and special tasks relevant to animal conservation. In total, we include 13 tasks spanning 7 major animal categories and 819 species, comprising a total of 41,839 data entries. To construct Animal-Bench, we devise a pipeline for automated data filtering and question-answer pair generation, reducing human effort and mitigating potential biases from human intervention. Furthermore, since our data primarily originates from the web, which typically features favorable

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recording conditions, while real-world filming scenarios may involve harsh weather conditions such as snowy or frosty, or changes in shooting parameters, such as variations in camera distance and direction due to animal movements. To accommodate potential variations in model applications and simulate real-world filming conditions, we employ video editing methods for simulation. As illustrated in Figure 1, previous editing-based evaluation benchmark [34] generated images that did not correspond to real situations and were not applicable to our setting. We utilize a video editing approach based on the diffusion model [35] to simulate videos captured in realistic scenarios, thereby evaluating the robustness of multimodal video models. We evaluate 8 existing multimodal video models on our benchmark, identifying significant room for improvement. We hope our work can inspire advancements in multimodal video models development.

Benchmarks	**Dataset Properties**			**Tasks**
	Label	QA Size	Agent(main)	
Video-MME [36]	Multi-Choice QA	2700 QAs	Human & Object	object, action, attribute, position, count, time, reasoning, summarization, etc.
Video-Bench [11]	Multi-Choice QA	15,033 QAs	Human & Object	action, object, attribute, position, count, time, reasoning, etc.
MVBench [3]	Multi-Choice QA	4000 QAs	Human & Object	action, object, position, count, scene, pose, attribute, character and cognition
Animal Kingdom [37]	Classification	N/A	Animal	object, action, time
MammalNet [38]	Classification	N/A	Animal	object, action
Animal-Bench	Multi-Choice QA	41,839 QAs	Animal	Common tasks: object, action, time, count, reasoning Special tasks: predator-prey behavior monitoring, social interaction analysis, breeding behavior monitoring and stress and pain detection

Table 1: Comparison of existing video understanding benchmarks. In contrast to other benchmarks, Animal-Bench mitigates the limitations of prior video question-answering benchmarks that lack animal agents. The dataset is characterized by its richness and diversity, facilitating a comprehensive evaluation of models across multiple dimensions of performance.

2 Related Work

MLLM Benchmarks Traditional evaluation benchmarks [39, 40, 41, 42, 43] typically only test the ability of models by a single task. With the rise of multi-modal large language models (MLLMs), new benchmarks [44, 13, 9] aimed to cover a wider range of evaluation aspects. For instance, Video-Bench [11] categorized the video language models' comprehension abilities into three levels: video-exclusive understanding, prior knowledge-based question-answering, and comprehension and decision-making. The Perception test [45] focused on skills (memory, abstraction, physics, semantics) and types of reasoning (descriptive, explanatory, predictive, counterfactual) across video, audio, and text modalities. These benchmarks all evaluated whether the models' capabilities were comprehensive enough by carefully choosing and dividing tasks, while overlooking the importance of data selection for evaluation. Other works considered how data selection influenced the evaluation process. For Image-LLM evaluation, MMBench [10] hierarchically subdivided the MLLM models' perception and cognition abilities and redesigned the QA pairs to better reflect capabilities of the models. For Video-LLM evaluation, MVBench [3] considered 20 challenging video tasks in its evaluations, selecting 200 test instances from open datasets for each task and redesigning the QAs. However, most existing benchmarks used human-centric data, predominantly featuring humans as the main agents and neglecting others. Our Animal-Bench believes that MLLMs should demonstrate good generalization abilities across different agents, thus designing a new benchmark and assessing the performance of MLLMs on animal-centric data.

Editing-based Benchmarks In recent years, some works have employed editing techniques to process benchmarks, enhancing data diversity and evaluating model robustness. Regarding benchmarks based on image editing, LANCE [46] utilized image editing techniques to augment the test set with a suite of diverse, challenging, yet counterfactual examples for diagnosing the image recognition abilities of different models. D. Hendrycks's work [47] established a rigorous benchmark for testing image classifier robustness by introducing diverse types of corruptions and perturbations, including

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noise, blur, weather effects, and digital distortions. For benchmarks based on video editing, Grover et al.[48] established an occluded dataset and further developed the benchmark to explore the impact of occlusion on action recognition models. Schiappa et al.'s work[49] proposed a robustness analysis by introducing 90 perturbations that reflected different real-world distribution shifts in their benchmark, offering insights into robust video action recognition. However, most of these works were counterfactual or only considered the effects of camera disturbances from the camera's viewpoint, neglecting factors such as scene characteristics (e.g., shooting distance and direction) that are likely to be encountered in real filming scenarios. Inspired by the aforementioned studies, Animal-Bench employs video editing techniques to create new animal videos under varying weather conditions and shooting parameters, presenting new demands and challenges for model robustness.

3 Methods

In this section, we will introduce the details of our Animal-Bench. In the first part, we describe how our Animal-Bench is designed in terms of task definition and the automated pipeline of data processing. The second part details our approach to editing videos in our benchmark, aiming to simulate realistic scenarios.

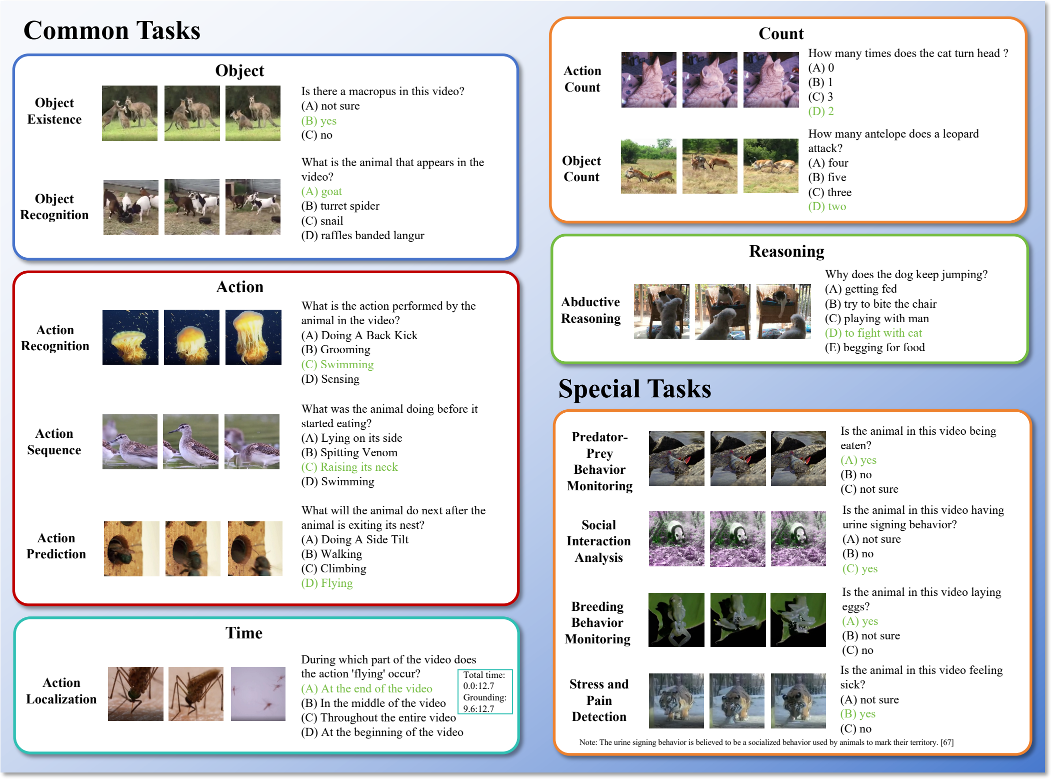
Common Tasks
Object
Object Existence
Is there a macropus in this video?
(A) not sure
(B) yes
(C) no
Object Recognition
What is the animal that appears in the video?
(A) goat
(B) turret spider
(C) snail
(D) raffles banded langur
Action
Action Recognition
What is the action performed by the animal in the video?
(A) Doing A Back Kick
(B) Grooming
(C) Swimming
(D) Sensing
Action Sequence
What was the animal doing before it started eating?
(A) Lying on its side
(B) Spitting Venom
(C) Raising its neck
(D) Swimming
Action Prediction
What will the animal do next after the animal is exiting its nest?
(A) Doing A Side Tilt
(B) Walking
(C) Climbing
(D) Flying
Time
Action Localization
During which part of the video does the action 'flying' occur?
(A) At the end of the video
(B) In the middle of the video
(C) Throughout the entire video
(D) At the beginning of the video
Total time: 0.0:12.7
Grounding: 9.6:12.7
Count
Action Count
How many times does the cat turn head ?
(A) 0
(B) 1
(C) 3
(D) 2
Object Count
How many antelope does a leopard attack?
(A) four
(B) five
(C) three
(D) two
Reasoning
Abductive Reasoning
Why does the dog keep jumping?
(A) getting fed
(B) try to bite the chair
(C) playing with man
(D) to fight with cat
(E) begging for food
Special Tasks
Predator-Prey Behavior Monitoring
Is the animal in this video being eaten?
(A) yes
(B) no
(C) not sure
Social Interaction Analysis
Is the animal in this video having urine signing behavior?
(A) not sure
(B) no
(C) yes
Breeding Behavior Monitoring
Is the animal in this video laying eggs?
(A) yes
(B) not sure
(C) no
Stress and Pain Detection
Is the animal in this video feeling sick?
(A) not sure
(B) yes
(C) no
Note: The urine signing behavior is believed to be a socialized behavior used by animals to mark their territory. [67]

Figure 2: Example demonstrations of each task in Animal-Bench

3.1 Animal Bench: Animal-Centric Evaluation

3.1.1 Animal-Centric Tasks System

To evaluate the perceptual and cognitive abilities of multimodal large models on data where animals serve as the main agents, our Animal-Bench redefines tasks that were previously overlooked in human-centric benchmarks. First, we consider the common tasks from human-centric evaluations to assess the models' abilities in "object", "action", "time", "count", and "reasoning" on videos featuring animals. Additionally, from the perspective of application value, we identify specific tasks related to animals that are of greater interest to zoologists. For instance, we focus on models' ability to detect predator-prey behaviors [50], social interactions [51], breeding behaviors [52], and stress and

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pain [53], thereby promoting better research and protection of animals. As shown in Figure 2, we designed the following tasks:

Common Task Perception: Object. (1) Object Existence(OE): Judge whether a certain item exists during a particular video; (2) Object Recognition(OR): Determine the specific class of the object that appears in the video. Action. (3) Action Recognition(AR): Recognize the action performed by the animal based on a piece of video; (4) Action Sequence(AS): Infer the action of an animal before or after a certain action in chronological order; (5) Action Prediction(AP): Given a specific action and its starting and finishing time in the video, predict the subsequent action performed by the animal; (6) Action Localization(AL): Assess the start and end time of a specific action performed by the animals in the video. Count. (7) Action Count(AC): Calculate how many times an action has been performed in the video; (8) Object Count(OC): Calculate how many times an object appears in the video. Cognition: (9) Reasoning(RS): Logically infer why an event or a certain scenario occurred in the video.

Specific Task (10) Predator-Prey Behavior Monitoring(PM): Detecting the interactions between predators and their prey that influence survival strategies, such as hunting techniques and evasion tactics; (11) Social Interaction Analysis(SA): Analyzing behaviors occurring between animals that affect social structure, communication, and cooperation; (12) Breeding Behavior Monitoring(BM): Monitoring activities related to reproduction, including mating and caregiving for offspring; (13) Stress and Pain Detection(PD): Detecting physiological and psychological responses to harmful stimuli or adverse conditions that impact the welfare and behavior of animals.

3.1.2 Animal-Centric Data Processing Pipeline

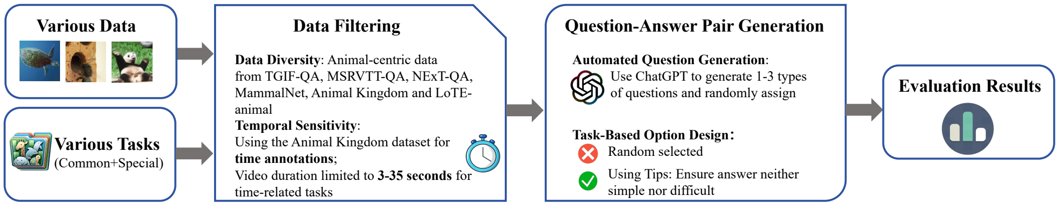
Various Data
Various Tasks
(Common+Special)
Data Filtering
Data Diversity: Animal-centric data from TGIF-QA, MSRVTT-QA, NExT-QA, MammalNet, Animal Kingdom and LoTE-animal
Temporal Sensitivity:
Using the Animal Kingdom dataset for **time annotations**;
Video duration limited to **3-35 seconds** for time-related tasks
Question-Answer Pair Generation
Automated Question Generation:
Use ChatGPT to generate 1-3 types of questions and randomly assign
Task-Based Option Design:
Random selected
Using Tips: Ensure answer neither simple nor difficult
Evaluation Results

Figure 3: The diagram of our animal-centric data processing pipeline: Firstly, choose dataset and identify tasks, then establish rules to filter data, and finally automatically generate QA pairs.

We develop an automated pipeline for processing animal-centric data. Initially, we conduct data filtering on the existing dataset according to predefined task definitions. Subsequently, we formulate rules to automatically generate questions and options for all data, culminating in a dataset structured in the multiple-choice question answering (QA) format. The rationale for adopting the multiple-choice QA format [54, 55, 56] is twofold. Firstly, regarding difficulty, this format alleviates the challenge of delineating the scope of options inherent in open-ended QA formats, while still presenting a substantial challenge to capabilities of models. Secondly, from the point of evaluation fairness, the multiple-choice QA format facilitates the calculation of final evaluation accuracy and enables effective comparison of different models' performance.

Data Filtering We first select data that aligns with the defined evaluation tasks. The principles for data selection are as follows. (1) Data diversity: Diverse data enables our evaluation to encompass a variety of complex situations, avoiding biases caused by single species or single dataset. (2) Temporal sensitivity: The temporal sensitivity present in the data allows us to assess the model's temporal modeling capabilities, as appropriate video lengths facilitate accurate decision-making for multi-modal video models.

To ensure the diversity of data, our Animal-Bench dataset is sourced from 6 datasets, encompassing 7 major animal categories, including mammals, insects, reptiles, amphibians, birds, fishes, and sea animals, totaling 819 different animal species. Specifically, for tasks related to "action", "object" and "time", we primarily get the annotated data for animals, actions, and grounding from MammalNet [38] and Animal Kingdom [37]. For the "count" and "reasoning" tasks, our evaluation data is sourced from open datasets such as TGIF-QA [57], MSRVTT-QA [42], and NExT-QA [40], from which we

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extract a substantial amount of data featuring animals as agents. For special tasks, due to the lack of annotated data, we select data with annotations that match the requirements of the tasks from Animal Kingdom, LoTE-animal [58], and MammalNet [38].

To ensure the temporal sensitivity of the data, we first select the Animal Kingdom dataset, which contains annotations relevant to video-grounding tasks. Specifically, it marks the time intervals of actions, facilitating our evaluation of tasks such as action prediction, action sequence, and action localization. Additionally, for tasks other than "object," we believe that correct answers cannot be obtained solely from spatial information but require temporal information. For these tasks, we constrain the video duration to between 3 to 35 seconds. This ensures that answering questions requires relevant temporal information without causing confusion for the model due to excessively long video lengths. Ultimately, the average duration of our benchmark videos is 14.61 seconds.

QA Pair Generation We have meticulously designed the generation rules for both the questions and the options. Here is the detailed process of our QA pair generation.

Automated Question Generation: For each task's description, we use ChatGPT [59] to generate 3 types of questions and randomly assign one of the generated questions to each piece of data.

Task-Based Option Design: (1) Directly adopt from existing QA annotation: For count and reasoning tasks, the options are directly chosen from the annotated multi-choice QA dataset. (2) Automatic option design: For other data without QA annotations, we automatically convert the original annotations into multi-choice QA format. For object existence tasks and special tasks, our options were set as "yes", "no", and "not sure". While for other tasks, options besides the right answer should be neither simple nor difficult in order to reflect the real perceptual ability of evaluated MLLMs, thereby our options should not be randomly chosen from the dataset. Specifically, for action-related tasks, considering the long-tailed distribution in the dataset, our four options consist of the correct answer, two options from the top 50% of most frequent answers, and one option from the least frequent 50% answers. For object recognition task, besides the right answer, two options are sampled from different major animal categories and one option is sampled from the same major animal category. This design ensures a balance in options. Once the options are set, they are randomly shuffled to ensure robustness of our evaluation. For a discussion on the option design rules, please refer to Appendix B.

3.2 Realistic simulation based on video editing

First, we select different aspects to simulate, as follows:

- **Weather conditions.** Weather changes are common during outdoor filming. In this work, we choose snowy and frosty weather as the simulated conditions. Snow is a form of precipitation that visually obstructs. Frost forms when ice crystals coat lenses or windows.
- **Shooting parameters.** Due to the camera's placement in the natural habitat of animals, the shooting parameters may vary due to animal movements. In this work, we select shooting distance (affected by the movements of animals resulting in changes in proximity to the camera) and shooting direction (affected by animal collisions resulting in camera tilt) as the simulated shooting parameters.

Simulating variations in outdoor weather conditions We take simulating snowy weather as an example. First, we assume that the snow layer S is an image with random noise, which follows a normal distribution $S \sim \mathcal{N}(\mu, \sigma^2)$. Next, we resize the image to make the density and distribution of snow more uniform. Since snowflakes do not accumulate in dark areas but only in well-lit areas when they fall on an object's surface, we set a threshold t and remove parts below it. Specifically, we can express it as:

$$S' = \begin{cases} \text{zoom}(S, f) & \text{if zoom}(S, f) \geq t. \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Finally, we apply a blur effect to the snow layer to soften its edges. The blur operation can be expressed as:

$$S_{blurred}(x, y) = \frac{1}{2\pi\sigma^2} \sum_{i=-r}^{r} \sum_{j=-r}^{r} e^{-\frac{i^2+j^2}{2\sigma^2}} \cdot S'(x - i, y - j), \tag{2}$$

where, $S_{\text{blurred}}(x, y)$ denotes the pixel value after blurring. r denotes the blur radius. σ represents the standard deviation of the Gaussian kernel. i and j represent the indices of the convolution kernel.

Simulating variations in shooting parameters We aim to simulate different shooting distances from the camera to animals, as well as shooting directions. To simulate proximity, we achieve this through central cropping of each frame. However, when simulating remoteness or different shooting directions, we face the challenge of lacking broader context outside the current frame. To address this issue and enhance the realism of our video evaluations, we leverage the capabilities of the Diffusion model [60] to perform outpainting for regions beyond the original scene. Furthermore, we have developed an automated video editing pipeline to streamline this process.

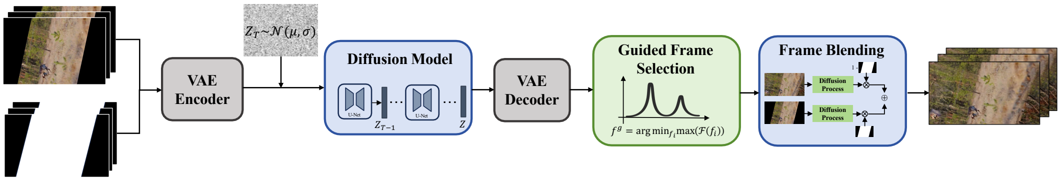

Figure 4: The diagram of simulation process for shooting parameters. Firstly, the transformed images along with their masks are encoded, and then passed through the diffusion model for denoising. After decoding, the final simulated video is obtained through the guided frame selection module and frame blending module.

For a video frame $f \in \mathcal{R}^{3\times H\times W}$, we perform scaling or rotational transformations on it using an orthogonal matrix. Scaling and rotation matrices can be represented as follows,

$$T_S = \begin{pmatrix} \text{scale} & 0 \\ 0 & \text{scale} \end{pmatrix} \quad T_R = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}. \tag{3}$$

Then we create a new blank canvas $f' \in \mathcal{R}^{3\times H\times W}$, which has the same center position as the original image. Then the part of the original video frame that remains on the new canvas after transformations is:

$$f'(x', y') = \begin{cases} f\left(T^{-1}(x', y')^T\right), & \text{if } T^{-1}(x', y')^T \text{ is within the bounds of } f \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

We encode f' and the mask of f' using a variational autoencoder [61] to derive their respective image embeddings y within the latent space. Subsequently, these embeddings, accompanied by initially sampled noise $\mathbf{z}_T \sim \mathcal{N}(0, \mathbf{I})$ drawn from a standard normal distribution, are jointly fed into denoising process. The reverse diffusion process is formulated as:

$$\mathbf{z}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{z}_t - \frac{\beta_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(\mathbf{z}_t, t, y) \right) + \sigma_t \mathbf{z}, \quad \mathbf{z} \sim \mathcal{N}(0, \mathbf{I}), \tag{5}$$

where α_t and β_t are predefined diffusion coefficients. $\epsilon_\theta(\mathbf{z}_t, t, y)$ is the predicted noise. σ_t is the noise standard deviation at each step. After obtaining the final latent space representation $\mathbf{z}_0$, the image is generated through the decoder, $\mathbf{x}_0 = \mathcal{D}(\mathbf{z}_0)$.

Due to the varying quality of outpainting generated by diffusion for each video frame, with some frames showing significantly better results than others, we observe that frames with smoother pixel transitions at the edges of the original image tend to have better outpainting quality. We hypothesize that the highest values in the image spectrum originate from the edges of the original outpainted image. Therefore, we select the frame with the smallest highest spectrum value as the guide image.

$$f^{\text{g}} = \arg\min_{f_i} \max(\mathcal{F}(f_i)), \quad \text{for} \quad f_i \in \{f_1, f_2, \ldots, f_n\} \tag{6}$$

If directly using the outpainting part in the f^{g} would cause slight misalignment at the edges of other frames. Inspired by [34], we blend images at different noise levels along the diffusion process using diffusion models. Starting from the outpainting part f^{g}, at each stage, we perform a guided diffusion step with a latent variable f_t^{g} to obtain f_{t-1}^{g}, while simultaneously obtaining a noisy version f_{t-1} of the original frame f. The f_{t-1} generated at this stage is a blend of two latent variables using a mask M, represented as follows.

$$f_{t-1} = M * f_{t-1} + (1 - M) * f_{t-1}^{\text{g}} \tag{7}$$

4 Experiments

In this section, we will sequentially introduce the details of our experimental implementation, the effectiveness of existing multimodal video models on our proposed evaluation benchmark, and their robustness on our editing-based realistic scenario simulation data. Finally, we will discuss the experimental results, hoping to provide guidance for model optimization.

4.1 Implementation details

We conducted all tests for multimodal video models on an NVIDIA RTX 4090 with 24GB of VRAM. To ensure fair comparisons, we standardize the 7B LLM backend versions used across all multi-modal video models tested during inference, thereby minimizing discrepancies in language proficiency due to differences in model sizes. Following the methodology outlined in [3], we establish a uniform system prompt and adopt the prompt-based model output matching strategy. All generated outputs successfully match the corresponding options. For each video, we sample 16 frames and resize them to (224, 224). During video editing, we utilize StableDiffusion-inpainting to expand the scenes beyond the captured footage and subsequently apply StableDiffusion-v1.5 for noise addition in frame blending.

4.2 Evaluation results

		Multimodal Video Model								
Task	Random 95% confidence interval	mPLUG -Owl [44]	Video Chat [62]	Video -ChatGPT [63]	Video -LLaMA [8]	Valley [64]	Chat -UniVi [65]	Video -LLaVA [4]	Video Chat2 [3]	Avg
OE	33.32 ± 0.46	42.20	49.40	44.65	49.20	41.70	44.65	45.90	50.00	45.96
OR	24.96 ± 0.19	33.62	51.61	24.31	60.23	25.06	43.25	40.55	86.75	45.67
AR	25.26 ± 0.17	27.00	32.54	24.28	35.34	24.56	32.98	31.71	66.27	34.34
AS	26.12 ± 1.23	25.86	32.76	22.41	29.74	27.16	33.19	25.86	54.31	31.41
AP	24.16 ± 1.31	25.48	27.88	24.52	29.81	28.37	27.88	28.37	50.00	30.29
AL	25.49 ± 0.39	24.49	23.25	21.22	24.67	25.45	24.14	24.32	21.22	23.60
OC	25.17 ± 1.18	24.14	27.59	24.71	26.44	25.29	31.61	31.03	64.94	31.97
AC	25.06 ± 0.37	24.43	25.51	22.92	24.99	23.78	24.34	22.49	29.16	24.70
RS	19.46 ± 0.71	22.38	27.07	25.69	35.08	22.65	36.46	21.27	68.23	32.35
					Special Task					
PM	33.58 ± 0.41	43.19	48.00	44.88	50.68	40.28	49.70	45.37	52.44	46.82
BM	33.63 ± 1.21	39.31	50.29	43.35	47.98	44.80	48.84	42.20	47.69	45.56
SA	33.22 ± 0.54	41.08	48.87	47.23	49.47	42.96	48.18	44.16	52.42	46.80
PD	33.15 ± 1.55	40.56	47.55	46.85	50.35	38.46	44.06	45.80	54.20	45.98
					Overall Performance					
Avg	27.89 ± 2.90	31.83	37.87	32.08	39.54	31.58	37.64	34.54	53.66	37.34

Table 2: The evaluation results of 8 multimodal video models on our Animal-Bench (the first place for each task is marked in red, and the second place is marked in blue, and those below random accuracy are marked in gray).

Effectiveness evaluation results The table 2 presents the evaluation results of eight existing multimodal video models on our Animal-Bench. As models evolve, their performance also improves. The recently released model VideoChat2 [3] surpasses previous methods in most tasks. Notably, VideoChat2 achieves an accuracy of 86.75% in object recognition tasks and 68.23% in reasoning tasks. However, we also observe shortcomings in existing models on certain tasks. For instance, in action localization and action counting tasks, the answers provided by existing models are nearly equivalent to random guesses. These tasks typically require strong temporal understanding capabilities, which cannot be inferred solely from spatial scene comprehension. This indicates a need for enhancement in the temporal modeling abilities of existing models. Additionally, in the object existence task, the models tend to respond with "yes", indicating a severe hallucination problem.

Robustness evaluation results We test the robustness of our models and their sensitivity to different types of variations on four types of simulated real-world data. We select the top four models in terms of effectiveness evaluation for robustness testing, as models with lower accuracy tend to provide responses close to random guessing, rendering discussions about robustness less meaningful. As shown in Table 2, VideoChat2 demonstrates relatively good robustness, with an overall decrease in accuracy of 3.70%. However, Video-LLaMA [8] shows sensitivity to the four simulated variations, with an overall decrease in accuracy of 8.72%. As depicted in Figure 5, we calculated the average accuracy decrease of the models for the four types of variations, revealing that models are more sensitive to shooting parameters than to changes in weather changes.

Models	**Weather condition**		**Shooting parameters**		**Overall**
	Snow	Frost	Distance	Direction	
VideoChat2	1.49	2.17	4.76	6.39	3.70
Video-LLaMA	5.41	7.46	10.82	11.19	8.72
VideoChat	7.43	4.41	5.22	8.63	6.42
Chat-UniVi	5.04	1.81	3.83	7.86	4.64

Table 3: Sensitivity of multimodal video models to different variations(relative accuracy drop(%)).

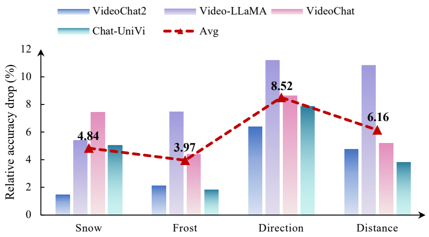

Figure 5: Average decrease in model accuracy(%) across four types of variations.

4.3 Further discussion

Video editing samples As shown in Figure 6, we demonstrate the effects of our video editing pipeline used for simulating shooting parameters. It can be observed that the guided frames obtained through spectrum filtering have initially achieved good results. However, there still exist unnatural transitions at the edges of the original image. After undergoing the diffusion noise addition process again, the edges of the original image can transition better into the newly generated parts of the image. Since we employed a frozen stable diffusion model, the generation effect relies on the performance of this model.

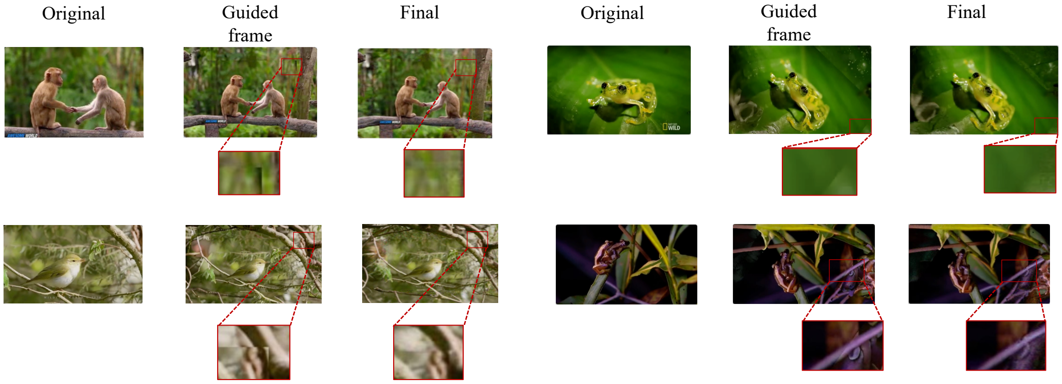

Figure 6: The visualization results of simulated changes in shooting parameters. Zoom in to view details.

Animal category bias We aim to investigate whether the models exhibit biases towards different animal categories. We analyze the performance of multimodal video models in two tasks: object recognition and action recognition. We choose these two tasks for analysis due to their involvement with the most diverse range of animal species. As shown in Figure 7, in the object recognition task, models demonstrate higher recognition accuracy for the "mammal" and "bird" categories, while accuracy is generally lower for categories like "amphibian" and "reptile". Similarly, in the action recognition task, models exhibit higher accuracy in recognizing "fish" and "mammal" categories.

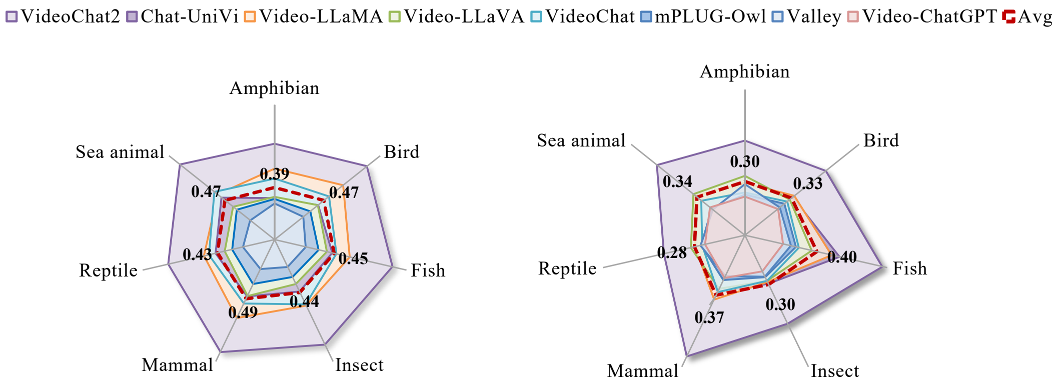

Figure 7: The radar map illustrates the accuracy on "object recognition" and "action recognition" tasks across 7 animal categories.

This could possibly be attributed to the greater prevalence of mammalian and fish species in the pretraining video datasets. Conversely, other categories suffer from lower recognition performance due to larger domain disparities.

Model structure We also analyze on the impact of model architecture on accuracy, we find from the data in Figure 8 that using the frozen CLIP ViT/L-14 [66] as the video encoder resulted in overall performance inferior to models employing larger or fine-tuned video encoders. This suggests that employing more powerful video encoders aids in a more comprehensive exploration of video features, which is of significant importance for the development of multi-modal video models. In addition, we observe that introducing a temporal modeling module into the model architecture is not particularly effective. According to Figure 8, models with an additional temporal modeling module outperform some earlier models in terms of answer accuracy but do not reach the level of some recently released models. This finding suggests that in the model design, the impact of the temporal modeling module may not be as significant as expected.

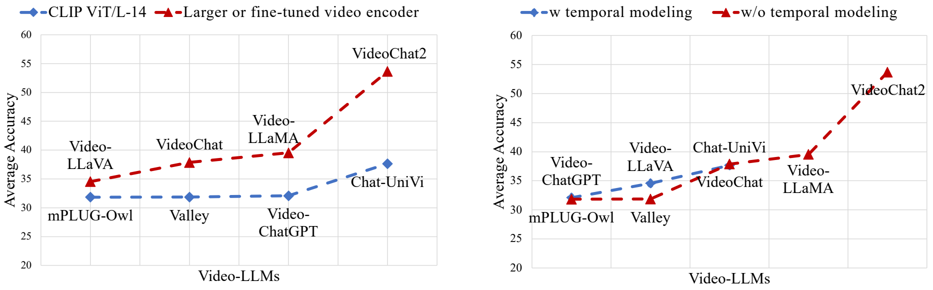

Figure 8: The line graph depicting the impact of video encoders and temporal modeling on the results.

5 Conclusion

In this work, we introduced Animal-Bench, an animal-centric benchmark to evaluate multimodal video models in real-world contexts. It includes 13 tasks across 7 major animal categories and 819 animal species. We proposed an automated pipeline of data processing. And we used video editing approaches to simulate realistic scenarios. We evaluated 8 current models on our Animal-Bench, and found significant room for improvement. We analyzed the bias of models towards animal categories and examined the influence of model architecture on experimental results. Our work aims to provide valuable insights and foster new research directions in multimodal video models.

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Appendix

A More Details on QA Generation

In Table 5, we provide a detailed breakdown of task divisions from coarse-grained to fine-grained levels, specifying the data used for each task. We have established specific rules for generating QA pairs based on the data requirements of different tasks. For tasks without existing QA pairs, we use ChatGPT [59] to automatically generate three questions and randomly select one to minimize model bias towards the questions. We also present the amount of data included for each task. Except for a few tasks, most tasks have sufficient data.

B Option Difficulty

Quantifying the difficulty of options is inherently challenging. In this study, we employ a qualitative analysis approach to achieve a moderate level of difficulty for the options. For the action recognition task, we examined the frequency of various actions and found that they adhere to a long-tail distribution. We categorize common actions, or "head actions," such as "running" and "eating," as simple options that can be identified without specialized knowledge. In contrast, rare actions, or "tail actions," such as "molting" in birds, require specialized knowledge to identify and are thus classified as difficult options. Our approach involves incorporating the correct answer along with two simple options and one difficult option, thereby ensuring that the difficulty of the options is balanced and reflective of the natural frequency distribution of actions. For the object recognition task, we test four situations:

- Random selection: Besides the correct answer, the other three options are randomly selected from all the animal species involved.
- Different major categories: Besides the correct answer, the other three options are randomly selected from different major animal categories than the correct answer. This setting makes the question-answer pairs easier because it is a coarse-grained judgment. The difference between the other three options and the correct answer is large, and if the model can identify correctly at the coarse-grained level, it can answer correctly.
- Same major category: Besides the correct answer, the other three options are randomly selected from the same major animal category as the correct answer. This setting makes the question-answer pairs more difficult because it is a fine-grained judgment. The difference between the other three options and the correct answer is small.
- Rules designed in this paper: Besides the correct answer, two options come from a different major animal category than the correct answer, and one option come from the same major animal category as the correct answer. This design makes the question-answer pairs neither too difficult nor too easy.

The comparative experimental results regarding the four rules are shown in Table 4. The results indicate that the selection of options affects the experiment results, which also supports our theoretical analysis above. Our design can moderate the difficulty of the question-answer pairs, making the evaluation of the model more aligned with real-world scenarios.

Rules	Acc (%)
Different major categories	97.31
Random selection	91.96
Same major category	76.34
Rules designed in the paper	86.75

Table 4: The table of accuracy rates of VideoChat2's responses for the four different option generation rules.

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	Ability	Coarse task	Fine-grained task	Datasets	Rules	Size
Common Task	Perception	Object	Object Existence	MammalNet	Q: Is there a/an (X) in this video? (X): 50% probability chosen from the GT labels 25% probability chosen from the other animals with the same mian class as GT 25% probability chosen from other classes compared with GT O: "yes", "no", "not sure"(shuffle)	2000
			Object Recognition	MammalNet Animal Kingdom	Q: Randomly select three sentence patterns generated by ChatGPT O: One option from the GT label One option from the the other animas with the same main class as GT Two options from other main classes compared with GT	15000
		Action	Action Recognition	MammalNet Animal Kingdom	Data: (1) Choose data that are with single action label annotation (2) 3 < Duration < 35 Q: Randomly choose one out of three ChatGPT-generated questions O: One option from the GT label Two options from the top 50% of most frequent actions One option from the least frequent 50% actions	15060
			Action Sequence	Animal Kingdom(VG)	Data: (1) Choose data which include only one kind of animal with more than two different actions (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT O: One option from the GT label Two options from the top 50% of most frequent actions One option from the least frequent 50% actions	232
			Action Prediction	Animal Kingdom(VG)	Data: (1) Choose data which include only one kind of animal with more than two different actions (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT O: One option from the GT label Two options from the top 50% of most frequent actions One option from the least frequent 50% actions	208
		Time	Action Localization	Animal Kingdom(VG)	Data: (1) Choose videos that do not contain repeated actions. (2) Split the video into three time zones (beginning/middle/end/throughout). Next, re-annotate the data into those labels by checking in which time zone the action lasts the longest. If the grounding occurs at the very beginning or end of the video and lasts longer than 50% of the total video length, it should be removed. (3) 3 < Duration < 35 Q: Randomly choose one out of three ChatGPT-generated questions O: "In the middle of the video." "Throughout the entire video." "At the end of the video.", "At the beginning of the video." (Shuffle)	1682
		Count	Object Count	MSRVTT-QA	Data: 3 < Duration < 35 Q, C: Utilize ChatGPT to adopt those animal-centric videos and annotations in MSRVTT-QA	174
			Action Count	TGIF-QA	Data: 3 < Duration < 35 Q, C: Utilize ChatGPT to adopt those animal-centric videos and annotations in TGIF-QA	2325
	Cognition	Reasoning	Abductive Reasoning	NExT-QA	Data: 3 < Duration < 35 Q, C: Utilize ChatGPT to adopt those animal-centric videos and annotations in NExT-QA	362
Special Task	Perception	Special Behavior Detection	Predator-Prey Behavior Detection	MammalNet Animal Kingdom	Data: (1) Choose data that include action of "hunts other animals","camouflaging" etc. (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT C: "yes", "no", "not sure" (shuffle)	1827
			Social Interaction Analysis	MammalNet Animal Kingdom LoTE-Annimal	Data: (1) Choose data that include action of "hugging","circumanal gland signing", "urine signing" and "aggregation" etc. (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT C: "yes", "no", "not sure" (shuffle)	2337
			Breeding Behavior Monitoring	MammalNet Animal Kingdom LoTE-Annimal	Data: (1) Choose data that include action of "parental", "mates with other animals", "gives birth to a baby" and "nurses or breastfeeds its baby" etc. (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT C: "yes", "no", "not sure" (shuffle)	346
			Stress and Pain Detection	MammalNet Animal Kingdom	Data: (1) Choose data that include action of "vomits" and “dying" (2) 3 < Duration < 35 Q: Sentence pattern generated by ChatGPT C: "yes", "no", "not sure" (shuffle)	286

Table 5: More details about how Animal-Bench divide tasks, filter data and process data into QA format.

C More Experiment Details

As shown in Table 6, we standardized the parameters of all language models used to ensure the fairness of the experiments. Following [3], we designed a uniform system prompt and answer prompt. By setting the answer prompt, our model outputs correspond to one of the options. In robustness testing, we selected 100 data samples from each task in the original Animal-Bench. Our selection process adhered to two principles: randomness, to minimize bias introduced by human intervention; and diversity, ensuring that the selected data represents the species in the original dataset. We believe that these data samples are sufficient to represent our original dataset and can reduce computational burden. We set different levels of severity for each variation. For weather changes, we set five variation parameters and randomly selected one for each piece of data. For size and angle changes, to simulate distant scenes, we set the ratio of the simulated video height to the original video height between $0.1 * (3 - 7)$; to simulate close scenes, we set the scale between $0.1 * (1.3 - 1.7)$. To simulate direction changes, we set the angle between $(30° - 90°)$ and $(270° - 330°)$ to mimic realistic conditions.

Parameters	**Value**
System Prompt	Carefully watch the video and pay attention to the cause and sequence of events, the detail and movement of objects, and the action and pose of animals. Based on your observations, select the best option that accurately addresses the question.
Question Prompt	Only give the best option.
Answer Prompt	Best option: (
Crop Size	(224, 224)
Number of Frames	16
Max Tokens	200
Temperature	1.0
Scale	$0.1 * (3 - 7), 0.1 * (13 - 17)$
Angle	$(30° - 90°), (270° - 330°)$

Table 6: Detailed Experimental Parameters.

D Ablation Study on Data Preprocessing

We conduct an ablation study on the number of video frames input to the model and the frame cropping method. We test with both 16 frames and 8 frames, designing two different video frame cropping settings.

Setting 1: The specific video preprocessing process is as follows: if $H > W$, the frame is scaled to $(224, 224 \times H/W)$. If $W > H$, the frame is scaled to $(224 \times W/H, 224)$. After scaling, the video frames are center-cropped to obtain a center region of $(224, 224)$.

Setting 2: We also experiment with padding non-square videos along the shorter side to make them square before scaling them to $(224, 224)$.

The experimental results are shown in Table 7. Reducing the number of frames leads to a decrease in the model's accuracy on most time-related tasks, which demonstrates that increasing the input video frames benefits the model in extracting temporal information and improving accuracy. However, in the object counting task, reducing the number of frames results in a significant performance improvement. We believe this is because the MSRVTT-QA dataset used for object counting contains video segments from different perspectives within a single video. These different perspectives may capture various states of instances, and increasing the number of frames could confuse the model when processing redundant information from different perspectives, making it difficult to distinguish between instances. We also find that using the padding-then-cropping video frame preprocessing method leads to a slight decrease in the model's accuracy.

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Methods	OE	OR	AR	AS	AP	AL	OC	AC	RS	PM	BM	SA	PD	Avg
num=16, Setting 1	50.00	86.75	66.27	54.31	50.00	21.22	64.94	29.16	68.23	52.40	47.69	52.42	54.20	53.66
num=8, Setting 1	50.00	86.67↓ 0.08	65.88↓ 0.39	54.74↑ 0.43	46.15↓ 3.85	21.28↑ 0.06	69.54↑ 4.6	28.95↓ 0.21	67.40↓ 0.83	52.40	47.69	52.42	54.20	53.64↓ 0.02
num=16, Setting 2	50.00	85.13↓ 1.62	64.72↓ 1.55	51.72↓ 2.59	50.96↑ 0.96	22.17↑ 0.95	62.64↓ 2.30	28.99↓ 0.17	66.57↓ 1.66	52.30↓ 0.01	47.69	52.42	54.20	53.04↓ 0.62

Table 7: Ablation study results table for data preprocessing.

E Results on MSRVTT-QA and TGIF-QA

We also analyze the models' performance on all data from MSRVTT-QA and TGIF-QA, as well as the animal subset data from Animal-Bench, as shown in Table 8. The model performs better on the overall data but worse on the animal subsets. This indicates, to some extent, that the model exhibits agent bias, demonstrating a stronger understanding of videos with humans and objects as agents compared to those with animals as agents.

Method	MSRVTT-QA		TGIF-QA	
	Original All Data	Animal-Bench (Object Count)	Original All Data	Animal-Bench (Action Count)
VideoChat	45.0	27.6	34.4	25.5
Video-LLaMA	29.6	26.4	–	25.0
Video-ChatGPT	49.3	24.7	51.4	22.9
Video-LLaVA	59.2	31.0	70.0	22.5

Table 8: Experimental results comparison on MSRVTT-QA, TGIF-QA, and Animal-Bench (object count and action count).

F Multimodal Video Model Parameters

In Table 9, we present a comparison of the parameters of the multimodal video models used in our experiments. We provide a detailed description of the model parameters from aspects such as video encoder, temporal module, large language model, training datasets, and the size of the training datasets. By analyzing these alongside the experimental results, we obtain several discussions on the model structure in the main part of the paper. In addition to the discussions on the video encoder and temporal module mentioned in the main paper, we also find that the amount of training data does not significantly affect the experimental results; a larger training dataset does not necessarily lead to better model performance, and vice versa. We hope these findings on the impact of model structure and training process on experimental results can inspire future development of multimodal video models.

G Data Statistics on Different Agents

In Fig. 9, we present statistics on the agents involved in each task of MVBench. It can be observed that most tasks only include human agents or objects interacting with humans, with very few tasks involving animal agents. This further illustrates that existing evaluation benchmarks are biased towards humans, and the evaluation of multimodal video models in the domain of animals is lacking.

We have calculated the occurrence frequency of each animal species in our Animal-Bench dataset, as depicted in Figure 10. It can be observed that the distribution of animals is not uniform, following a long-tail distribution, which aligns with the general pattern where some species are more abundant while others are less so in the natural world.

MLLMs	Video Encoder	Temporal Module	LLM	Training Dataset	Training Dataset Size
mPLUG-Owl	CLIP ViT/L-14	/	LLaMA-7B	stage 1: LAION-400, MCOYO-700M, Conceptual Captions, MSCOCO stage 2: ALpaca, Vicuna, Baize, LLaVA	stage 1: 1105M stage 2: 392K
Video-ChatGPT	CLIP ViT/L-14	/	Vicuna-7B	video instruction pairs	100K
Valley	CLIP ViT/L-14	Temporal attention, Temporal token	Stable-Vicuna-7B	stage 1: CC595K, WebVid2M stage 2: video, image based instruction data (combined, LLaVA, Video-ChatGPT)	stage 1: 1297K stage 2: 234K
VideoChat	ViT-G/14	Global Multi-Head Relation Aggregator	Stable Vicuna-7B	stage 1: WebVid-10M, COCO, Caption, Visual Genome, SBU Captions, CC3M, CC12M stage 2: part of MiniGPT-4, LLaVA	stage 1: 25M stage 2: 18K
Chat-UniVi	CLIP ViT-L/14	Dynamic visual token	Vicuna-7B	stage 1: image-caption pairs (COCO, CC595K) stage 2: MiMIC-IT, LLaVA, Video-ChatGPT	stage 1: 595K stage 2: —
Video-LLaMA	ViT-G/14	/	Vicuna-7B	stage 1: Webvid-2M, CC595K stage 2: MiniGPT-4, LLaVA, Video-ChatGPT	stage 1: 2M stage 2: 649K
VideoChat2	UMT-L	/	Vicuna-7B	stage 1: CC3M, CC12M, WebVid-10M stage 2: COCO, Visual Genome, SBU, InternVid stage 3: 6 categories	stage 1: 15M stage 2: 12M stage 3: 1.9M
Video-LLaVA	ViT-L/14 + LoRA finetune	/	Vicuna-7B	stage 1: LAION-CC-SBU, WebVid stage 2: LLaVA, Video-ChatGPT	stage 1: 1260K stage 2: 765K

Table 9: Comparison of parameters of different multimodal video models, where "/" indicates that no trainable temporal modules are introduced.

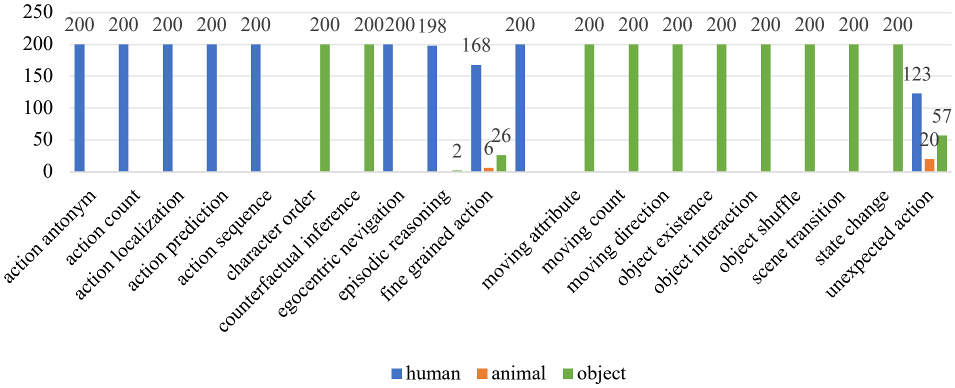

Figure 9: The data quantity for different agents in each task of MVBench.

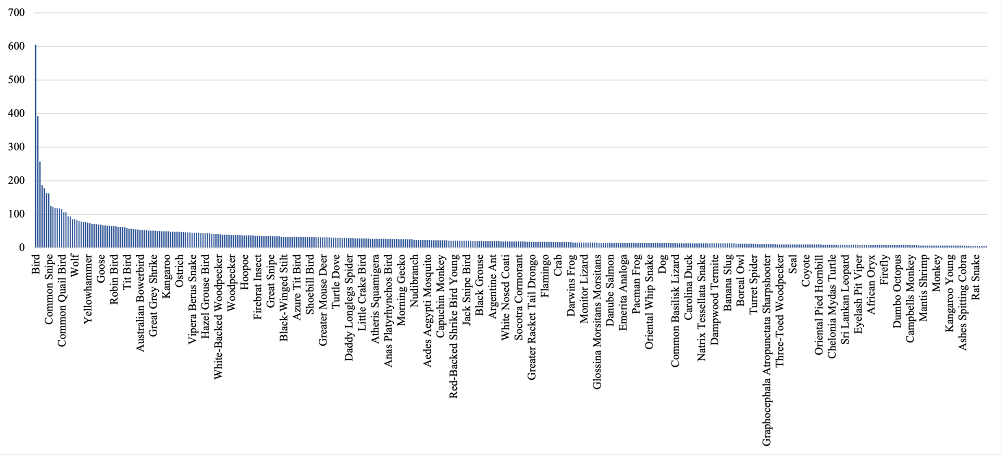

Figure 10: Statistical chart of data quantities for different animal species.

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H Potential Negative Impacts

Although the technology itself is intended to protect and study wildlife, if it falls into the hands of malicious actors, it could be used for illegal hunting, poaching, and animal exploitation. These actions could cause severe damage to wildlife populations and make conservation efforts more challenging. Also, excessive reliance on technology for animal monitoring and protection may lead to neglect of manual patrols and traditional conservation methods. If the technology fails or is compromised, it could result in serious security vulnerabilities. Given these potential negative impacts, it is recommended to implement strict security measures in technology application and data management, and to establish appropriate laws and regulations to ensure the technology is used correctly and safely.

I Limitations and Future Directions

Our work has some limitations: First, the responses of multimodal video models may be influenced by the input parameters of the models, and different parameter settings could affect the accuracy of the responses. We did not test the sensitivity of the model to these parameters and instead used uniform parameters for the models. Second, since our editing is based on stable diffusion, the editing effect is subject to the capabilities and limitations of stable diffusion. Third, video editing may introduce some counterfactuals or additional animals that could change the answers to the questions. We have made efforts to minimize this occurrence through manual selection. In future work, we will continue to study the impact of model parameters on model performance and conduct deeper research on diffusion models to achieve better editing effects. We also plan to reduce the appearance of new animals in the future by adding negative prompts and conducting further exploration.

J Assets and Licenses

In our paper, we use data from six datasets: Animal-Kingdom [37], MammalNet [38], LoTE-Animal [58], MSRVTT-QA [42], NExT-QA [40], and TGIF-QA [57]. We appreciate the contributions of the aforementioned works, all of which have been cited in the main article. Specifically:

- MammalNet is licensed under the CC BY license.
- LoTE-Animal is licensed under the Creative Commons Attribution-ShareAlike 4.0 International License.
- MSRVTT-QA is licensed under the MIT license.
- NExT-QA is licensed under the MIT license.
- For the Animal-Kingdom dataset, we have contacted the authors by filling out a questionnaire regarding the dataset's use and have obtained an official download link. Additionally, we have emailed the authors about our use of the dataset in our paper.
- The TGIF-QA dataset is explicitly stated on its GitHub page "to be free to use for academic purposes only."

We believe that our work fully respects the original authors' copyrights, and all assets have been used appropriately.

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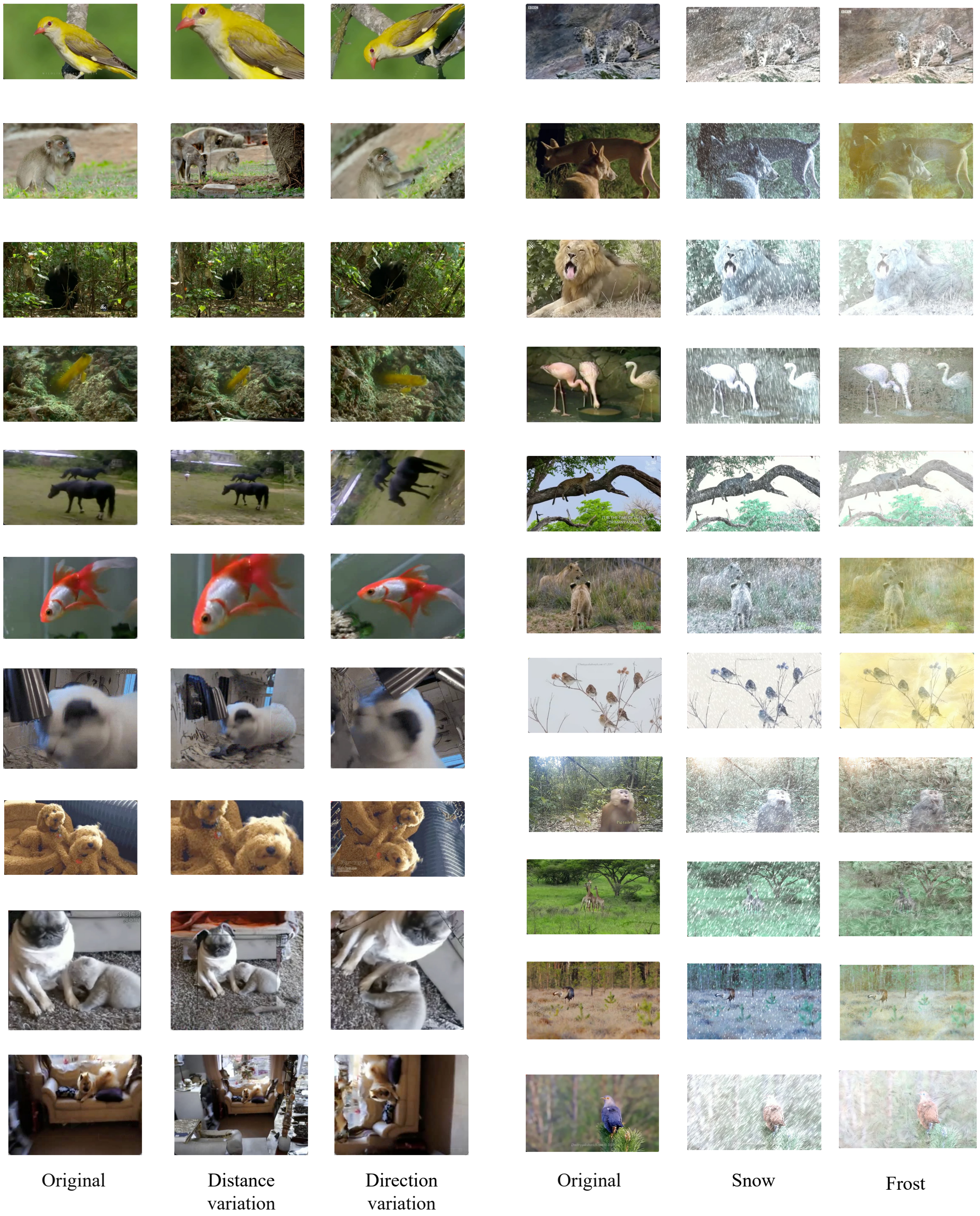
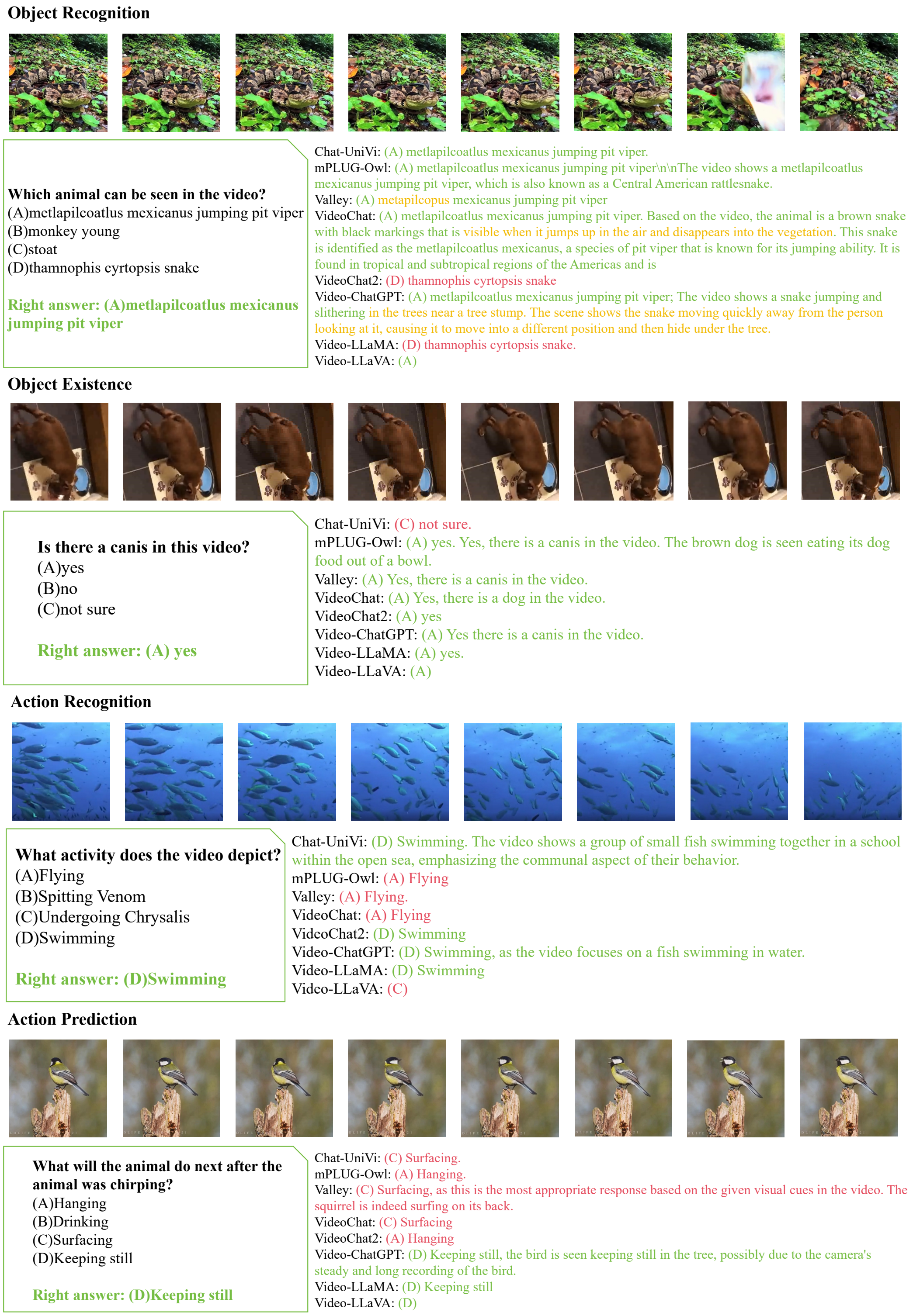


Figure 11: Visualization of simulated changes mimicking real shooting scenarios



Object Recognition

Which animal can be seen in the video?
(A)metlapilcoatlus mexicanus jumping pit viper
(B)monkey young
(C)stoat
(D)thamnophis cyrtopsis snake

Right answer: (A)metlapilcoatlus mexicanus jumping pit viper

Chat-UniVi: (A) metlapilcoatlus mexicanus jumping pit viper.
mPLUG-Owl: (A) metlapilcoatlus mexicanus jumping pit viper\n\nThe video shows a metlapilcoatlus mexicanus jumping pit viper, which is also known as a Central American rattlesnake.
Valley: (A) metapilcopus mexicanus jumping pit viper
VideoChat: (A) metlapilcoatlus mexicanus jumping pit viper. Based on the video, the animal is a brown snake with black markings that is visible when it jumps up in the air and disappears into the vegetation. This snake is identified as the metlapilcoatlus mexicanus, a species of pit viper that is known for its jumping ability. It is found in tropical and subtropical regions of the Americas and is
VideoChat2: (D) thamnophis cyrtopsis snake
Video-ChatGPT: (A) metlapilcoatlus mexicanus jumping pit viper; The video shows a snake jumping and slithering in the trees near a tree stump. The scene shows the snake moving quickly away from the person looking at it, causing it to move into a different position and then hide under the tree.
Video-LLaMA: (D) thamnophis cyrtopsis snake.
Video-LLaVA: (A)

Object Existence

Is there a canis in this video?
(A)yes
(B)no
(C)not sure

Right answer: (A) yes

Chat-UniVi: (C) not sure.
mPLUG-Owl: (A) yes. Yes, there is a canis in the video. The brown dog is seen eating its dog food out of a bowl.
Valley: (A) Yes, there is a canis in the video.
VideoChat: (A) Yes, there is a dog in the video.
VideoChat2: (A) yes
Video-ChatGPT: (A) Yes there is a canis in the video.
Video-LLaMA: (A) yes.
Video-LLaVA: (A)

Action Recognition

What activity does the video depict?
(A)Flying
(B)Spitting Venom
(C)Undergoing Chrysalis
(D)Swimming

Right answer: (D)Swimming

Chat-UniVi: (D) Swimming. The video shows a group of small fish swimming together in a school within the open sea, emphasizing the communal aspect of their behavior.
mPLUG-Owl: (A) Flying
Valley: (A) Flying.
VideoChat: (A) Flying
VideoChat2: (D) Swimming
Video-ChatGPT: (D) Swimming, as the video focuses on a fish swimming in water.
Video-LLaMA: (D) Swimming
Video-LLaVA: (C)

Action Prediction

What will the animal do next after the animal was chirping?
(A)Hanging
(B)Drinking
(C)Surfacing
(D)Keeping still

Right answer: (D)Keeping still

Chat-UniVi: (C) Surfacing.
mPLUG-Owl: (A) Hanging.
Valley: (C) Surfacing, as this is the most appropriate response based on the given visual cues in the video. The squirrel is indeed surfing on its back.
VideoChat: (C) Surfacing
VideoChat2: (A) Hanging
Video-ChatGPT: (D) Keeping still, the bird is seen keeping still in the tree, possibly due to the camera's steady and long recording of the bird.
Video-LLaMA: (D) Keeping still
Video-LLaVA: (D)

Figure 12: The illustrative sample of the generated responses from different multimodal video models for "object recognition", "object existence", "action recogntion" and "action prediction" tasks. Green indicates correct answers, red indicates incorrect answers, and orange indicates that although the chosen option is correct, there are some errors in the response.

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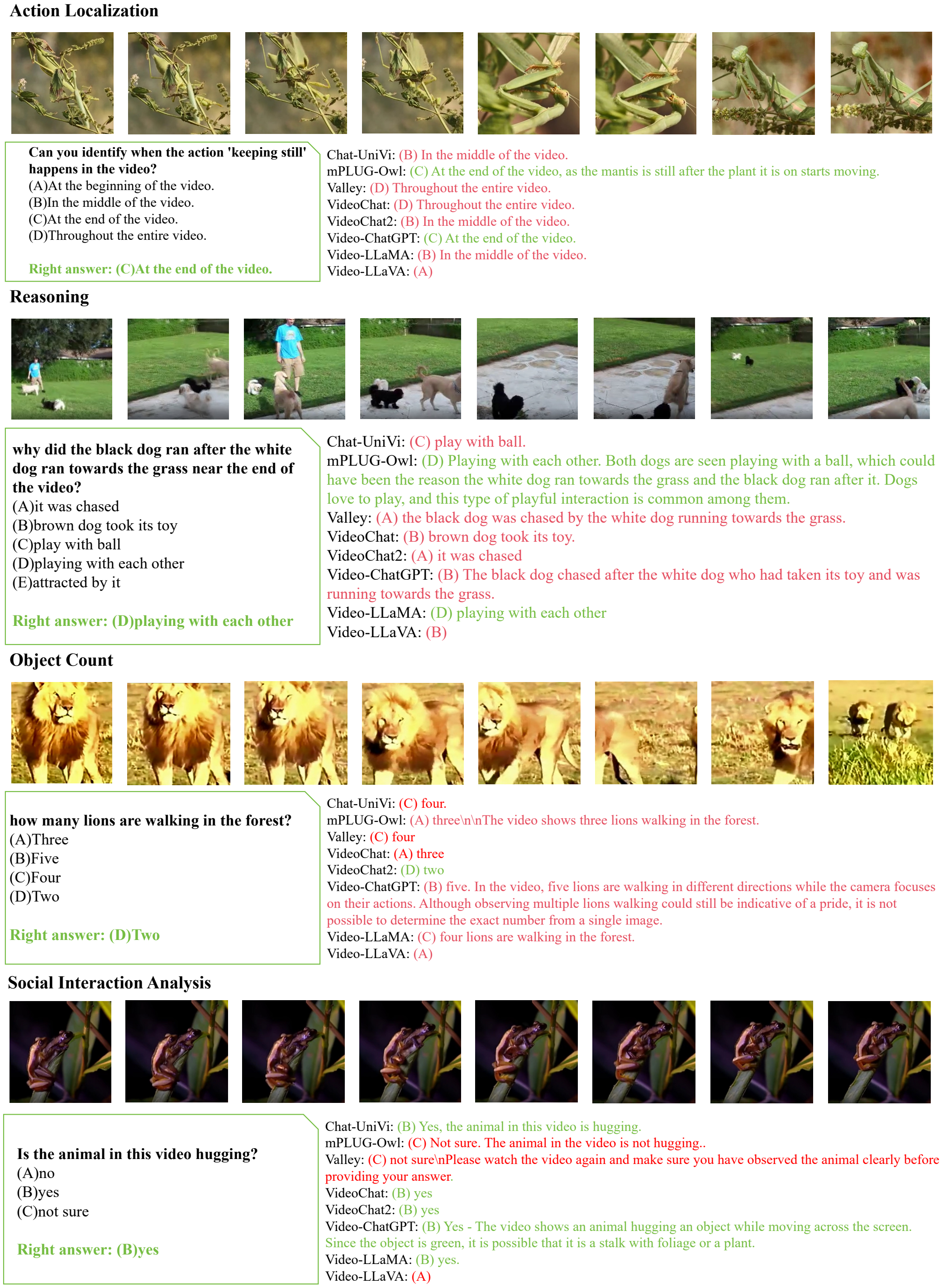

Action Localization

Can you identify when the action 'keeping still' happens in the video?
(A)At the beginning of the video.
(B)In the middle of the video.
(C)At the end of the video.
(D)Throughout the entire video.

Right answer: (C)At the end of the video.

Chat-UniVi: (B) In the middle of the video.
mPLUG-Owl: (C) At the end of the video, as the mantis is still after the plant it is on starts moving.
Valley: (D) Throughout the entire video.
VideoChat: (D) Throughout the entire video.
VideoChat2: (B) In the middle of the video.
Video-ChatGPT: (C) At the end of the video.
Video-LLaMA: (B) In the middle of the video.
Video-LLaVA: (A)

Reasoning

why did the black dog ran after the white dog ran towards the grass near the end of the video?
(A)it was chased
(B)brown dog took its toy
(C)play with ball
(D)playing with each other
(E)attracted by it

Right answer: (D)playing with each other

Chat-UniVi: (C) play with ball.
mPLUG-Owl: (D) Playing with each other. Both dogs are seen playing with a ball, which could have been the reason the white dog ran towards the grass and the black dog ran after it. Dogs love to play, and this type of playful interaction is common among them.
Valley: (A) the black dog was chased by the white dog running towards the grass.
VideoChat: (B) brown dog took its toy.
VideoChat2: (A) it was chased
Video-ChatGPT: (B) The black dog chased after the white dog who had taken its toy and was running towards the grass.
Video-LLaMA: (D) playing with each other
Video-LLaVA: (B)

Object Count

how many lions are walking in the forest?
(A)Three
(B)Five
(C)Four
(D)Two

Right answer: (D)Two

Chat-UniVi: (C) four.
mPLUG-Owl: (A) three\n\nThe video shows three lions walking in the forest.
Valley: (C) four
VideoChat: (A) three
VideoChat2: (D) two
Video-ChatGPT: (B) five. In the video, five lions are walking in different directions while the camera focuses on their actions. Although observing multiple lions walking could still be indicative of a pride, it is not possible to determine the exact number from a single image.
Video-LLaMA: (C) four lions are walking in the forest.
Video-LLaVA: (A)

Social Interaction Analysis

Is the animal in this video hugging?
(A)no
(B)yes
(C)not sure

Right answer: (B)yes

Chat-UniVi: (B) Yes, the animal in this video is hugging.
mPLUG-Owl: (C) Not sure. The animal in the video is not hugging..
Valley: (C) not sure\nPlease watch the video again and make sure you have observed the animal clearly before providing your answer.
VideoChat: (B) yes
VideoChat2: (B) yes
Video-ChatGPT: (B) Yes - The video shows an animal hugging an object while moving across the screen. Since the object is green, it is possible that it is a stalk with foliage or a plant.
Video-LLaMA: (B) yes.
Video-LLaVA: (A)

Figure 13: The illustrative sample of the generated responses from different multimodal video models for "action localization", "reasoning", "object count" and "social interation analysis" tasks. Green indicates correct answers, red indicates incorrect answers, and orange indicates that although the chosen option is correct, there are some errors in the response.

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- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

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Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Section 4.1 and the "More Experiment Results" part in appendix of the paper provides a detailed description of the experimental details.

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Justification: We present the 95% confidence intervals for the random results in Table 2 to demonstrate significantly lower results compared to random selection.

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