VideoGameQA-Bench: Evaluating Vision-Language Models for Video Game Quality Assurance

Mohammad Reza Taesiri
University of Alberta, CA
mtaesiri@gmail.com

Abhijay Ghildyal
Sony Interactive Entertainment, Aliso Viejo, US
abhijay.ghildyal@sony.com

Saman Zadtootaghaj
Sony Interactive Entertainment, Berlin, Germany
saman.zadtootaghaj@sony.com

Nabajeet Barman
Sony Interactive Entertainment, London, UK
nabajeet.barman@sony.com

Cor-Paul Bezemer
University of Alberta, CA
bezemer@ualberta.ca

Abstract

With video games now generating the highest revenues in the entertainment industry, optimizing game development workflows has become essential for the sector's sustained growth. Recent advancements in Vision-Language Models (VLMs) offer considerable potential to automate and enhance various aspects of game development, particularly Quality Assurance (QA), which remains one of the industry's most labor-intensive processes with limited automation options. To accurately evaluate the performance of VLMs in video game QA tasks and determine their effectiveness in handling real-world scenarios, there is a clear need for standardized benchmarks, as existing benchmarks are insufficient to address the specific requirements of this domain. To bridge this gap, we introduce VideoGameQA-Bench, a comprehensive benchmark that covers a wide array of game QA activities, including visual unit testing, visual regression testing, needle-in-a-haystack tasks, glitch detection, and bug report generation for both images and videos of various games. Code and data are available at: https://asgaardlab.github.io/videogameqa-bench/.

1 Introduction

The global video game industry continues to expand rapidly, with its market value projected to reach $257 billion by 2028 [11]. Alongside this substantial growth, the process of developing high-quality video games remains inherently complex and demanding. A critical challenge within game development is to ensure visual quality and consistency through a rigorous visual testing and quality assurance (QA) process. Automation of visual QA tasks remains particularly challenging [6, 23, 25, 29, 31, 37, 39, 43–45, 47, 55, 67] and currently, most visual QA relies heavily on manual inspection, making the process time-consuming, costly, labor-intensive, and prone to human error [35, 36].

The visual QA process for video games can generally be abstracted into three main types of tasks: (1) **verifying scene integrity** by comparing the visual representation of scenes against intended configurations and known reference states, such as an oracle (Fig. 1-a) or previously rendered versions of the same scenes (Fig. 1-b); (2) **detecting glitches** through open-ended exploration—these glitches are unintended gameplay (Fig. 1-e) or visual artifacts (Fig. 1-h) without specific reference points, requiring testers to rely on common sense and general knowledge for detection; and (3) **systematically**

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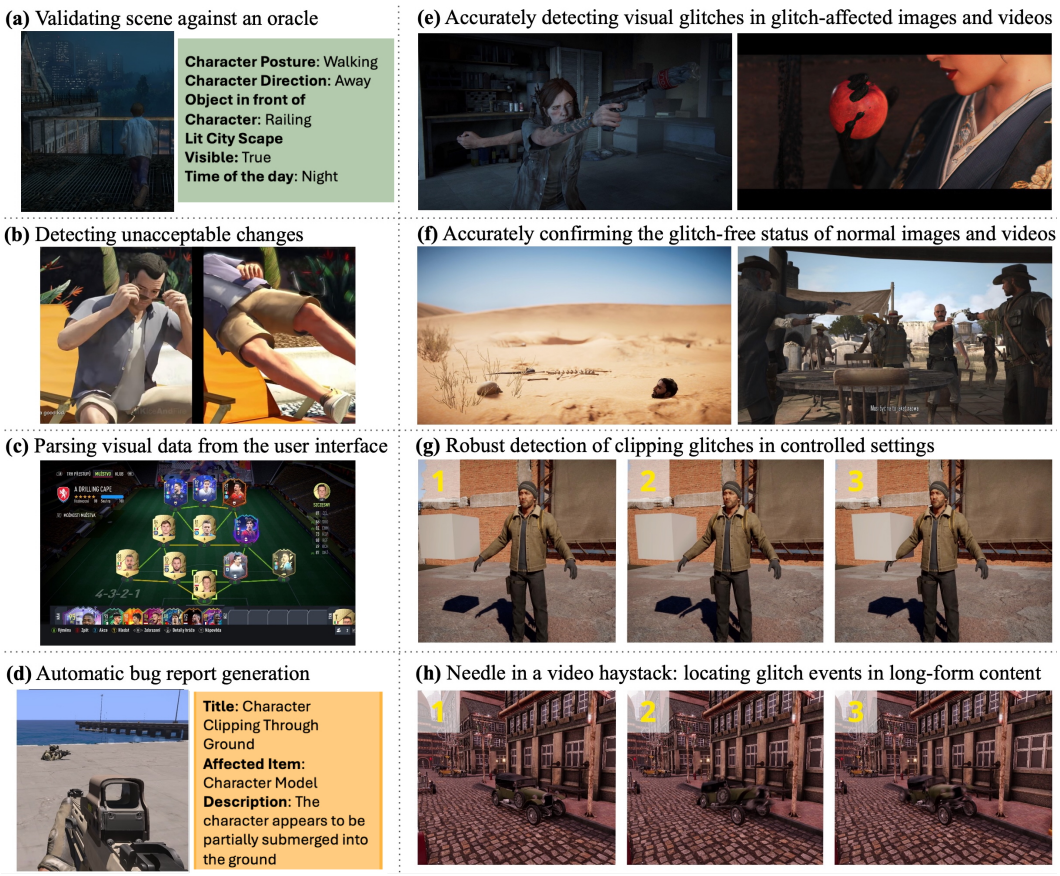

Figure 1: Sample tasks from `VideoGameQA-Bench`. (a) A **unit test** where the model should verify small details in the image, such as character's orientation and background. (b) A **visual regression test** where the model should detect unacceptable changes between two versions of the same scene. (c) A **UI unit test** in which the model must visually verify user interface components, such as a chemistry graph between players. (d) A **bug report generation task** where the model needs to generate a bug report for a glitch. (e) Two **glitch detection** tasks, where the model must identify visual anomalies, such as unnatural body configuration (left) or object clipping (right, fingers clipping the apple). (f) Two **glitch detection** tasks, where the model is required to verify the glitch-free status of images with intentional object clipping and high scene complexity. (g) A **parametric test** that evaluates whether the model can detect clipping at various object proximities. (h) A **needle-in-a-haystack task**, which requires the model to identify the first frame in which a glitch occurs.

reporting and documenting all identified glitches (Fig. 1-d) , ensuring developers receive clear and actionable information to address problems effectively during game development.

Recent advancements in vision-language models (VLMs) [3, 9, 16, 32, 68] present promising opportunities to automate and significantly enhance the efficiency of video game QA. However, progress in applying VLMs to game QA has been limited by the lack of standardized benchmarks. Current multimodal benchmarks tend to focus heavily on complex mathematical or textual reasoning tasks [27, 61, 62], overlooking essential visual comprehension tasks fundamental to video game QA. Similarly, existing game-specific benchmarks [5, 45–47] often represent only narrow aspects of QA tasks, thus inadequately evaluating and tracking VLM performance across diverse QA scenarios.

In this paper, we introduce `VideoGameQA-Bench`, a benchmark designed to fill the gap in evaluating VLMs for video game QA. Our key findings and contributions are as follows:

1. We present `VideoGameQA-Bench` featuring 9 distinct tasks and 4,786 questions designed considering real-world video game development scenarios, such as visual unit testing, regression testing, UI validation, video needle-in-a-haystack, and glitch detection.

2. While VLMs show promising performance on various multimodal benchmarks and can function as OCR systems, they perform poorly at detecting fine details required for accurate scene understanding and parsing complex UI elements. (Sec. 5.1)
3. Frontier VLMs show good performance on the glitch detection task using images (up to 82.8%) and videos (up to 78.1%); however, all struggle when it comes to glitches related to body configuration, intricate object clipping, and common-sense reasoning. (Sec. 5.2)
4. Visual regression testing remains one of the most challenging tasks for VLMs. (Sec. 5.3)
5. Locating specific glitch moments in videos remains a challenge, both in detecting and accurately pinpointing the glitch. (Sec. 5.4)
6. Frontier VLMs can generate useful bug reports for up to 50% of real-world glitches, providing accurate and descriptive summaries of the glitches. (Sec. 5.5)

2 Background

We use *glitch* as an umbrella term for unintended, user-visible anomalies that occur during gameplay. The anomalies we consider are visually evidenced in images or videos. This includes both (i) low-level graphical defects directly observable in pixels and (ii) higher-level scene inconsistencies that violate physics, gameplay logic, or common sense but still manifest visually (e.g., an NPC floating mid-air). Non-visual anomalies (e.g., audio-related anomalies) are out of scope for our evaluation.

To balance clarity for readers, we group glitches into two broad families based on how they appear in images or videos; the categories are not mutually exclusive, and a single failure can exhibit traits of both. We make this choice to help readers interpret the examples more easily, since industry taxonomies—often organized by underlying cause such as rendering, physics, or AI logic—do not always align with what can be directly observed in visual data.

Graphical glitches : Local, pixel- or geometry-level failures in image formation that degrade visual fidelity without necessarily changing the intended scene semantics.

- Missing or corrupted assets/textures: gray/purple "checkerboard" materials, blacked-out meshes, texture swimming/smudging (Appendix F.1).
- Geometry and rasterization issues: z-fighting, exploded or inside-out meshes, vertex normal errors, shadow acne (Appendix F.2).
- Temporal instability: flicker between LODs/materials, aliasing or shimmer that persists across frames (Appendix F.3).
- Post-processing and UI artifacts: ghosting, overdraw halos, HUD elements duplicated/misalaligned, compression/mipmap artifacts (Appendix F.4).

Logical (semantic) glitches: Visually coherent pixels arranged into scenes that violate physics, gameplay rules, or commonsense, yielding contextually incorrect outcomes.

- Physics and collision failures: character or props intersecting walls ("clipping"), falling through floors, floating objects, zero-gravity actors (Appendix F.5).
- Animation/state errors: frozen T-poses, limb contortions, mocap desync, ragdolls snapping upright, rapid teleportation/jumps (Appendix F.6).
- World and rule violations: doors open with no trigger, enemies spawn inside the player, items duplicate or vanish without effect (Appendix F.7).

3 `VideoGameQA-Bench`

We designed `VideoGameQA-Bench` 's tasks by simulating realistic QA scenarios encountered during actual video game development. However, to make the benchmark more relevant for future QA automation tasks, we also included tasks that may challenge current software engineering practices while also remaining highly relevant. Tab. 1 gives an overview of the contents of each task. In summary, `VideoGameQA-Bench` contains 2,236 image-based samples and 1,200 video-based samples from more than 800 games and 9 synthetic game scenes.

3.1 Tasks

Image-Based Tasks

1. **Visual unit testing**: Visual unit tests verify visual attributes including presence, placement, positioning, colors, conditions, and other relevant properties of various image elements.
2. **UI unit testing**: UI (visual) unit tests verify in-game UI elements such as menus, subtitles, heads-up displays (HUDs), and interface components like graphs and charts. We simulate the (UI) unit testing tasks by asking the VLM questions about game screenshots.
3. **Visual regression testing**: Visual regression tests check for unintended visual changes after a change to the game. A simple pixel-by-pixel comparison of two screenshots is not sufficient, as some variations (e.g., because of character customization or weather conditions in the game) may be acceptable. Visual regressions may occur in cinematic parts of the game, such as cutscenes that have a defined sequence flow. We simulate this task by asking the VLM to compare whether two screenshots are similar, taking into account the specified (un)acceptable variations.
4. **Glitch detection**: Glitch detection is the process of identifying unintended visual errors, such as rendering issues, clipping, or physics/logical bugs that express themselves visually. We simulate this task by asking the VLM whether glitch and glitch-free images contain a glitch.
5. **Parametric clipping detection**: Given the common occurrence of clipping in games, our benchmark includes a dedicated task to evaluate a model's ability to detect such glitches. In this task, images feature an object (e.g., a cube, sphere, or character) positioned at varying distances from a human character – from far apart to fully overlapping/clipping. The VLM is asked whether it detects clipping across each of these distances.
6. **Bug report generation**: In addition to testing/detection tasks, a potential application of VLMs is to assist QA engineers with writing reports for detected bugs. We simulate this task by asking the VLM to write a description of a glitch image that can be used in a bug report.

Video-Based Tasks

1. **Glitch detection**: Glitch detection in videos can be done to verify (autonomous) gameplay sessions from bots. Detecting glitches in videos is significantly more complex due to challenges such as analyzing motion (patterns), and may require identifying transient glitches that appear only briefly in a few frames. We simulate this task by asking the VLM whether it detects a glitch in a video.
2. **Needle-in-a-haystack (NIAH)**: NIAH is a more challenging long-context retrieval [53, 66] version of the glitch detection task. We simulate this task by asking the VLM whether it detects a glitch in a video, and in which frame the glitch occurs for the first time.
3. **Bug report generation**: In this task, the VLM is asked to provide a description of a glitch video that can be used in a bug report.

3.2 Data Collection

We constructed `VideoGameQA-Bench` using real-world and synthetic sources to ensure diversity, realism, and controlled conditions. We next detail the composition and collection processes for each data type. It should be noted that the data collection process was solely carried out by researchers from the University of Alberta.

Real-world samples: We sourced real-world data for the visual & UI unit testing, glitch detection and bug report generation tasks. For image-based tasks, we gathered diverse screenshots from the Steam Community ( ) image gallery. To find images with possible glitches, we used keyword search to find recent images tagged with the word "bug". For the video-based glitch detection task, we utilized gameplay videos from the GamePhysics ( ) dataset [45]. To complement this set with glitch-free videos, we randomly extracted 15-second gameplay videos—matching the median duration of videos in the GamePhysics dataset—from gameplay walkthroughs available on YouTube ( ). We also randomly selected 100 images and 100 videos from these sets for the bug report generation task.

Synthetic samples: We used the Unity ( ) game engine to create synthetic samples for tasks requiring controlled settings. For the clipping detection task, we systematically varied the spatial proximity

Table 1: Overview of tasks, their data sources, and expected format/contents of the responses to the questions in `VideoGameQA-Bench`. All responses must be formatted in JSON.

Type	Task	*N*	Source	Diversity	Annotation	Expected Response	Samples
Image	Visual unit	100		92 games		Object properties	Appendix H.1
	UI unit	100		94 games		UI properties	Appendix H.2
	Visual regression	250		9 scenes		Pass/fail	Appendix H.3
	Glitch detection	1,000		507 games		Detected/not detected	Appendix H.4
	Parametric clipping det.	686		9 scenes, 4 games		Clipping/not clipping	Appendix H.5
	Bug-report generation	100		61 games		Free-format description	Appendix H.6
Video	Glitch detection	1,000		778 games		Detected/not detected	Appendix H.7
	NIAH	100		9 scenes		Detected/not detected + frame number	Appendix H.8
	Bug-report generation	100		70 games		Free-format description	Appendix H.9

between 3D objects within Unity scenes. A human character model is positioned centrally, and we incrementally moved other objects—including a cube, sphere, 2D plane, and another character—from an initial distance of 15 units towards the central character. This movement continued progressively until the objects fully clipped into and became embedded within the character model.

For the NIAH task, we created 50-second gameplay clips in Unity and intentionally injected glitches as the "needle" at known timestamps. For this set, we used four types of glitches: (1) *flickering*, which causes parts of a game object to flicker rapidly; (2) *sudden disappearance*, where an object suddenly vanishes; (3) *object jump*, where a game object is rapidly thrown into the air; and (4) *missing texture*, where the texture of a game object is missing.

Mix of real-world and synthetic samples: For the visual regression testing task, we combine Unity-generated content with cutscene glitches sourced from YouTube videos. We selected nine distinct scenes from the Unity Asset Store, generating modified versions by randomly removing specific objects. We then paired captured images from these modified scenes with images from their unaltered reference versions. We further augmented this set with 70 glitch instances from cutscenes in various games on YouTube. Here, frames from glitched cutscene recordings were matched with corresponding frames from the glitch-free cutscenes, creating a dataset of paired frames.

3.3 Data Annotation and Label Verification

Manual annotation and verification: We (👨‍💻) manually reviewed the collected images and videos, labeling them as either glitch or glitch-free. For bug report generation, we include a brief description of the glitch.

We followed a multi-step verification process, regardless of existing labels or annotations. All images and videos underwent a sequential review involving three authors to validate their quality and confirm accurate labeling. This process helped prevent the propagation of incorrect annotations from previous datasets into `VideoGameQA-Bench`.

VLM and human in the loop: Visual unit tests and UI unit tests require constructing both the question and the answer. For these tasks, we used Gemini-2.5-Pro (✦) to initially draft a set of questions based on comprehensive instructions (Appendix B). We then analyzed the drafted questions, merged and refined them, and fixed the ground truth to create a final question based on the initial samples provided by Gemini-2.5-Pro.

Automated annotation: For synthetic data generated via Unity, we exported annotations directly from the Unity game engine. This ensured exact alignment between the annotations and the visual state of the images or videos, precisely indicating the presence or absence of glitches. For example, for the NIAH samples, a dedicated C# script systematically starts the recording, injects a glitch at a random timeframe, and exports both the videos and timestamps.

JSON structure: To facilitate interoperability and automation, we explicitly enforce that all ground truth labels (and therefore, each expected model output) in our dataset are valid JSON objects. To

guide the models toward the desired JSON schema, each question includes an empty JSON template, and we instruct the model to return its final response in that format.

To avoid suppression of chain-of-thought (CoT) [54], we include a *Reasoning* field in the JSON response, allowing the model to use the allocated space to "think" [2] before returning the response for tasks that require heavy reasoning. All tasks, except for visual (UI) unit tests, contain this field.

4 Experiments

VLMs: We evaluated a total of 11 proprietary and 5 open-weight models on `VideoGameQA-Bench`. Our evaluation includes both standard models and those designed for extended reasoning [1, 8, 42, 58].

Prompting videos: Only the Gemini family accepts video as a native input format; other models process videos as sequences of frames. To evaluate non-Gemini models, we sample one frame per second for all video-based tasks. For open-weight models, we reduce the sampling rate to ensure they can handle the images (see Appendix A for details).

Video frame sampling rate: We adopted a uniform sampling strategy of 1 FPS, meaning that each second of gameplay contributes one frame to the evaluation input, ensuring fairness across models with varying input constraints.

Glitch visibility at low FPS: Since most evaluated models cannot process long frame sequences, we standardized video sampling at 1 FPS. To verify that this downsampling does not obscure anomalies, we manually reviewed a subset of glitch-containing videos and found that in 95% of cases, the glitch remained clearly visible at 1 FPS.

Valid JSON output: All benchmark questions explicitly require models to output responses in a valid JSON format. Any responses not in JSON or containing malformed JSON structures will be disregarded, even if the model's output is only slightly different from the ground truth label.

LLM-as-a-judge: Both bug-reporting tasks require models to generate descriptive bug reports based on provided glitchy images or videos. Evaluating these reports poses challenges due to their open-ended nature, making human verification or an LLM-based judge necessary. Following recent literature [17], we use an LLM-based judge, specifically the OpenAI o3 model, to assess the accuracy of the generated reports by comparing them to textual ground truth references detailing the glitches. Details about prompt construction are available in Appendix E.

Model ranking: We ranked models by averaging accuracies across image and video tasks. Task-wise accuracies were first averaged within each type, then combined for the final score.

Details regarding model inference and prompt design are provided in Appendices A, C and D.

5 Results

Tab. 2 summarizes results across all benchmark tasks; we highlight key findings and examine model strengths and limitations in the remainder of this section. All models reliably produced task-specific JSON outputs, with malformed responses being rare and mostly limited to complex UI and unit-test tasks. Detailed statistics on model refusal rates and malformed outputs are provided in Appendix G.3.

5.1 VLMs Mostly Fail to Detect, Translate, and Represent Intricate Scene Details

Why does this matter: In software engineering, *unit tests* are assertions that verify an isolated piece of code behaves as intended. Applying the same discipline to rendered frames is equally valuable: *visual unit tests* can assert that the appearance and on-screen text of visual elements (including the UI) meet a specification. VLMs could make this practical: when prompted with a specific image, they can describe fine-grained visual details (e.g., a character's attire or pose) and read textual elements. This capability would allow tests to compare these outputs against reference descriptions, flagging mismatches early in the pipeline.

Results: Our experiments show that VLMs consistently struggle with fine-grained details, particularly when tasked with translating specific details and properties of objects, as well as reading charts, text,

Table 2: Accuracy (%) scores of models on `VideoGameQA-Bench`. **VU**: Visual unit testing; **UI**: UI unit testing; **VR**: Visual regression testing; **IGD**: Image-based glitch detection; **PCD**: Parametric clipping detection; **IBR**: Image-based bug report generation; **VGD**: Video-based glitch detection; **NIAH**: Needle-in-a-haystack; **VBR**: Video-based bug report generation. Numbers highlighted with † indicate that the score for the NIAH task was set to 0. The *Total* column shows the mean of the average scores from the image and video tasks.

	Image						Video			Average		
	VU	UI	VR	IGD	PCD	IBR	VGD	NIAH	VBR	Img.	Vid.	Total
Model / # Samples	100	100	250	1,000	686	100	1,000	100	100	2,236	1,200	3,436
GPT-4.1	43.0	28.0	28.8	81.3	**87.8**	51.0	75.8	19.0	51.0	**53.3**	48.6	**51.0**
GPT-4.1-mini	42.0	30.0	20.4	76.8	66.9	46.0	71.8	10.0	26.0	47.0	35.9	41.5
GPT-4.1-nano	9.0	14.0	19.2	57.0	66.9	16.0	49.1	4.0	14.0	30.4	22.4	26.4
GPT-4o	39.0	23.0	31.6	**82.8**	82.5	**54.0**	57.0	1.0	**52.0**	52.2	36.7	44.4
o4-mini	50.0	35.0	**45.2**	76.4	65.0	38.0	70.0	18.0	28.0	51.6	38.7	45.1
o3	43.0	28.0	39.6	73.7	80.5	53.0	76.8	13.0	45.0	53.0	44.9	48.9
Gemini-2.5-Pro	**53.0**	**40.0**	30.8	75.4	72.2	33.0	**78.1**	34.0	36.0	50.7	**49.4**	50.0
Gemini-2.5-Flash	47.0	24.0	26.4	66.3	72.2	24.0	64.7	35.0	23.0	43.3	40.9	42.1
Gemini-2.0-Flash	44.0	28.0	12.0	68.1	78.0	20.0	54.5	**36.0**	26.0	41.7	38.8	40.3
Sonnet-3.7	23.0	22.0	24.0	65.1	76.4	29.0	66.9	31.0	22.0	39.9	40.0	39.9
Sonnet-3.5	23.0	29.0	14.0	70.1	72.9	33.0	61.2	27.0	26.0	40.3	38.1	39.2
Llama-4-Scout	32.0	23.0	13.6	55.8	71.6	8.0	58.6	–	5.0	34.0	21.2†	27.6†
Llama-4-Maverick	21.0	22.0	18.4	53.2	65.7	7.0	56.6	–	15.0	31.2	23.9†	27.5†
Gemma-3 (27B)	12.0	12.0	12.8	46.7	69.7	10.0	51.3	–	9.0	27.2	20.1†	23.6†
Mistral-Small-3.1 (24B)	15.0	17.0	25.6	59.7	62.5	9.0	61.4	–	14.0	31.5	25.1†	28.3†
Qwen-2.5-VL (72B)	38.0	27.0	21.2	70.0	76.0	19.0	47.9	–	17.0	41.9	21.6†	31.7†

and other information in the scene. On both the visual and UI unit testing tasks, all models perform poorly, with Gemini-2.5-Pro being the best model (53.0% on visual and 40.0% on UI unit testing).

VLMs often struggle with fine-grained scene understanding, especially when it comes to interpreting object configuration, spatial relationships, and subtle visual cues [19]. They frequently misinterpret character posture (e.g., number of visible eyes, hand position, or orientation), object placement (e.g., whether an object is inside or outside a room), and the state of elements like whether a car door is open or closed (Fig. A19). These errors are more pronounced when properties are small or visually ambiguous, though failures also occur in clearer scenarios. Even seemingly simple tasks—like determining the direction an object is facing or counting elements—often lead to inconsistent results, highlighting limitations in current model capabilities for detailed visual reasoning.

Despite the promising performance of VLMs for OCR tasks [30, 41], accurately extracting structured information from complex game UI elements remains a significant challenge. While VLMs handle plain text and simple interfaces like basic game menus reasonably well, their performance declines with layouts involving large tables, progress bars, and elements such as minimaps. Interpreting charts and graphs with interconnected nodes and edges is also unreliable, as models consistently struggle to follow edges in the graph and understand the information presented in this format (Fig. A20).

Our findings align with prior studies highlighting the limitations of VLMs in fine-grained perception and spatial reasoning [38, 49]. Improvements in spatial reasoning and localization are essential before VLMs can be reliably used in detail-sensitive tasks like visual (UI) unit testing.

5.2 VLMs Can Detect Many Visual Glitches, But Struggle with Certain Types

Why does this matter: Glitch detection is a core component of game QA, often requiring extensive manual review due to the complexity and variety of visual errors that can arise during gameplay [20]. Leveraging VLMs for glitch detection could greatly reduce the need for manual review.

Results: VLMs, especially proprietary ones, demonstrate good performance in identifying visual glitches (e.g., with GPT-4o achieving an accuracy of 82.8%). This shows a step forward in glitch detection capability: prior work showed that the best-performing model could reach a glitch detection accuracy of only 57.2% [47]. The best-performing open-weight model, Qwen-2.5-VL, achieves an accuracy of 70.0% matching the performance of Sonnet-3.5. In contrast, Gemma-3 labels nearly all samples as "glitch," resulting in 100% recall but less than 2% specificity. Conversely, Llama-4-

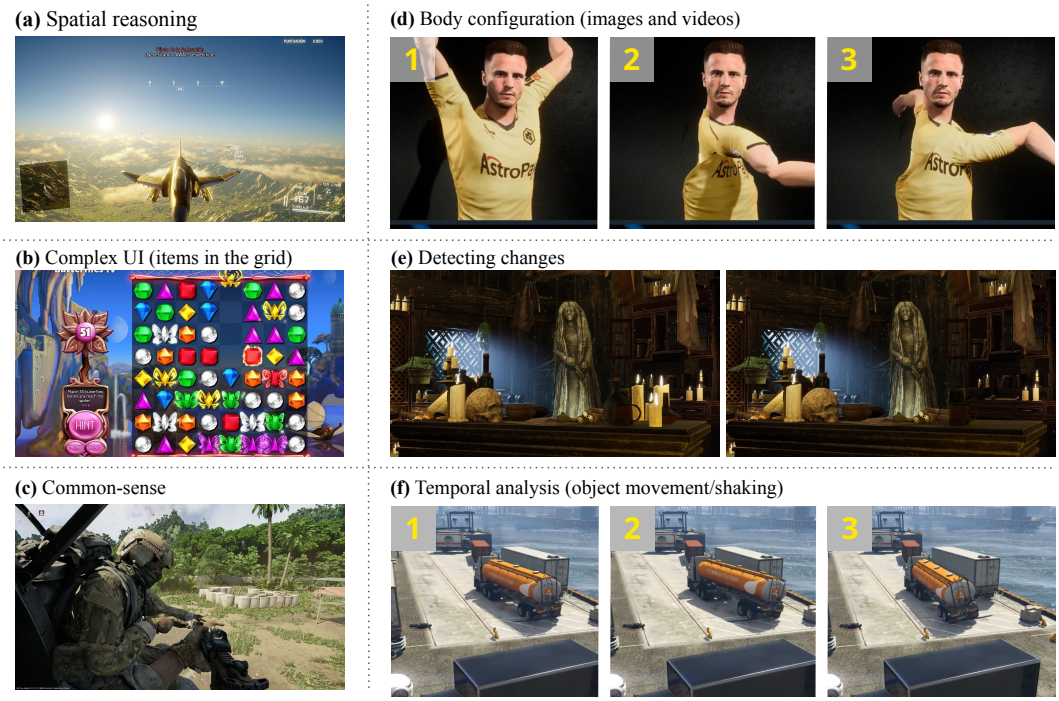

Figure 2: Samples from challenging cases that most VLMs consistently struggle with. (a) Failure to understand **spatial reasoning**, such as object orientation (whether an airplane is facing toward the camera or away). (b) Failure to read **UIs with complex layouts** and **objects arranged in grids**. (c) Failure to detect **common-sense inconsistencies**, such as a missing gun in the hand. (d) Failure to detect **unnatural body configurations**. (e) Failure to detect **missing foreground objects** (candles). (f) Failure to detect and analyze **object movement** such as shaking or bouncing.

Maverick and Llama-4-Scout label almost all samples as "clean," exhibiting recall at or below 14% and specificity exceeding 95%. Further details on performance metrics are provided in Appendix G.4.

In the video-based setting, Gemini-2.5-Pro achieves the highest performance at 78.1%. Compared to image-based tasks, proprietary models generally perform slightly worse on this task: GPT-4.1 (–5.5), o4-mini (–6.4), with the exception of o3 (+3.1) and Gemini-2.5-Pro (+2.7).

A major limitation observed across models in video-based glitch detection is that they process individual frames rather than entire videos natively, resulting in the loss of temporal context and audio signals (Fig. 2-f). Additionally, some models, such as GPT-4o, frequently refuse to generate valid responses to video-based queries.

During our manual analysis, we observed that certain types of visual glitches remain particularly challenging for even the best-performing model, in both image- and video-based settings:

1. **Unusual body configuration**: Characters appear with highly unnatural joint alignments or distorted poses, typically resulting from *ragdoll* physics simulations or incorrect animation states (e.g. an unusual position of hands or arms in Fig. 1-e and Fig. 2-d).
2. **Intricate object clipping**: Two or more objects intersect slightly, for example, characters rendered in overlapping positions, props penetrating hands, or limbs passing through solid geometry (e.g. an apple clipping with a hand in Fig. 1-e).
3. **Semantic glitches**: Contextual inconsistencies that require common-sense reasoning to interpret. For instance, a character may appear to be holding a weapon based on their posture, but the weapon is either missing or fails to render properly (Fig. 2-c).

We used o3 to identify common patterns among false-positive cases produced by the top-performing models. Specifically, we prompt o3 to summarize the *reasoning* field from the JSON outputs of GPT-4o, GPT-4.1, and Gemini-2.5-Pro. The most common false-positive patterns stem from model hallucinations about clipping glitches that do not actually exist (Appendices G.6 and G.8). To further

stress-test the models for clipping glitches, we conducted parametric clipping detection to analyze model behavior across various distances and complexities.

Our parametric test shows that while models can generally detect clipping glitches, they lack robustness. In particular, on borderline cases (i.e. where two objects only slightly overlap), models usually fail to recognize clipping issues. For example, although GPT-4.1 —achieving 87.8%—is the most robust model, it still consistently fails to detect such boundary cases (Appendix G.11).

Despite the improvements in glitch detection performance, fully autonomous glitch detection using only VLMs might not yet be feasible for real-world use. High false-positive rates (see Appendix G.4 for details) continue to pose a significant issue, potentially overwhelming human testers with unnecessary reviews, especially given that most frames in real-world gameplay are glitch-free. Additional considerations for real-world applicability are discussed in Appendix G.5.

5.3 VLMs Are Bad at Visual Regression Testing

Why does this matter: Verifying an image against a previously approved reference is a highly desirable form of testing in computer graphics and video games [13, 48, 50]. This need is especially acute in video games, where recurring sequences often include customizable elements, such as character appearances, or dynamic environmental changes like day/night cycles and weather variations. Recent advancements in image comparison capabilities of VLMs [3, 21, 63, 68] show that VLMs may be well-suited to this task because, through carefully designed prompts and in-context examples, we should be able to effectively *program* them to ignore permissible variations, such as changes in weather or lighting, while still verifying all other critical aspects of the image.

Results: Our results indicate that visual regression testing with VLMs does not yet perform well: o4-mini, the best-performing model, achieves an accuracy of 45.2%. Qualitative analysis further shows that all models consistently fail to detect a range of changes, whether subtle, like an object in the background (Fig. A39), or pronounced, close to the camera (Fig. 2-e).

A notable trend is that reasoning variants consistently outperform their non-reasoning counterparts within the same model family—for example, o3 versus GPT-4o (39.6% vs. 31.6%) and Sonnet-3.7 versus Sonnet-3.5 (24.0% vs. 14.0%). This trend does not appear in the glitch detection task. A plausible explanation is that a reasoning model can iteratively examine multiple aspects and objects in the two images before reaching a final decision; nevertheless, overall performance remains poor.

5.4 VLMs Can Detect Glitches in Gameplay Videos, but Struggle to Pinpoint Their Onset

Why does this matter: One of the goals in video game QA is to augment game-playing bots (e.g. using reinforcement learning [4]) with automatic glitch detection systems. Game-playing bots can interact with the game and generate many lengthy video recordings. A valuable capability in this context would be a system that can efficiently localize glitches in such videos.

Results: The results from the NIAH tasks indicate that most models struggle significantly with this task. Gemini-2.0-Flash and Gemini-2.5-Flash are the best-performing models, yet they achieve only 36.0% and 35.0% accuracy in locating the faulty frame within a 5-second error margin. This relatively low performance primarily stems from two factors: (1) the model completely fails to detect the glitch in the video, or (2) it detects that there is a glitch but fails to correctly locate the corresponding frames. For instance, GPT-4.1 detects glitches in 72 out of 100 videos (72% detection rate), but among these, it accurately locates the faulty frame in only 19 cases (26.5%)(see Appendix G.10).

5.5 VLMs Can Correctly Describe Glitches in Bug Reports for More Than Half of the Cases

Why does this matter: VLMs should be able to assist in the accurate documentation of glitches by generating bug reports of detected glitches, saving QA engineers a considerable amount of time.
Results: VLMs can generate accurate descriptions of more than half of the glitches in images and videos. In both settings, GPT-4o performs best, achieving 54.0% and 52.0% accuracy for images and videos, despite its poor glitch detection performance in videos (57.0%) due the high rate of request rejections. Nevertheless, these numbers suggest that for most models there is a 20–25% gap between their detection performance and ability to create accurate descriptions of glitches.

We reviewed bug reports that judges rejected as incorrect and identified four common patterns: **(1)** reporting non-existent glitches (hallucinations) or irrelevant objects; **(2)** failing to report all glitches in scenes with multiple glitches; **(3)** incorrectly concluding no glitch is present and **(4)** the model identifies the correct location/region of the glitch but fails to provide an accurate description.

We estimate that approximately 5% of judging outcomes are errors. In this task, we used the LLM-as-a-judge setting, which can introduce inaccuracies when calculating final model performance. After manually analyzing responses from several models, we found that these errors often occur when the judge is overly strict about exact wording and incorrectly rejects outputs that reference the glitch but differ slightly from the ground truth (Appendix G.14).

6 Related Work

Recent benchmarks show VLMs matching or exceeding human performance on various tasks (e.g. [7, 26, 27, 40, 60–62, 64, 65]). However, these benchmarks primarily test broad, curriculum-based worldly knowledge, providing limited insight into commonsense reasoning about physical interactions in visual media. Consequently, they inadequately assess understanding of physical and commonsense violations, such as video game glitches, highlighting the need for a new benchmark. PhysBench is the only recent study evaluating similar shortcomings by testing a broad range of physical concepts [10]. In contrast, our benchmark specifically addresses video game quality assurance, where question types and reasoning differ significantly due to game-specific characteristics. Identifying game glitches poses unique challenges that have received limited attention, except in GlitchBench [47], which our study supersedes through tailored evaluation tasks detailed in Sec. 3.

Video games sometimes exhibit distorted human anatomy due to physics failures, leading to unnatural poses from misaligned meshes and textures. Clipping is a common issue in which objects or limbs pass through each other. Previous game bug detection methods are not VLM-based and have limited ability to identify such glitches [12, 24, 29, 34]. While VLM-based image quality assessment methods [18, 22, 51, 56, 57, 59] use prompts to detect distortions, they struggle with semantic and structural anomalies [15]. A recent study proposed detecting such anomalies in generated images [28], focusing primarily on hallucinations in text-to-image models. In contrast, our work targets visual anomalies in video games that violate anatomical correctness, physical plausibility and commonsense.

7 Discussion, Limitations, and Conclusion

In this paper, we introduce `VideoGameQA-Bench`, a novel dataset for measuring and tracking the performance of vision-language models on video game quality assurance tasks. This dataset includes various real-world-related tasks that are directly useful for existing systems (e.g., glitch detection), video game testing pipelines, and potential future use cases (e.g., visual regression testing). Our results show that while VLMs generally perform well on other multimodal benchmarks, they are still not ready to be deployed for many video game QA tasks.

The samples in our benchmark primarily focus on glitches occurring after the game's release, as exact replication of glitches happening during development isn't possible since testing processes vary by company and game, and proprietary data is unavailable.

We acknowledge interest in extending the benchmark to interactive or agentic settings. However, current VLMs lack reliable end-to-end control and such setups require heavy, game-specific engineering. Given these limitations and the absence of standardized testbeds, we defer this component to future work, once models and tools better support interactive QA evaluation.

While inference-time scaling has been shown to improve performance in domains such as multimodal reasoning [33], longer test durations may render it impractical for our video game QA use cases. Nevertheless, we reported results on such models to illustrate the performance ceiling of current-generation models, even if they are not immediately deployable.

Although our benchmark focuses on games, many tasks closely align with anomaly detection in AI-generated content (AIGC) [14, 52]. Both domains involve identifying visual or semantic inconsistencies that violate physical or commonsense expectations. The same perceptual and reasoning abilities required to detect rendering or logic glitches in games are also essential for assessing the realism, and coherence of generative image and video systems.

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   Justification: Yes, we released the dataset as a public Hugging Face dataset. Other details about running the experiments using (vision) language models are provided in the main text and in the appendix.

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   - The answer NA means that paper does not include experiments requiring code.
   - Please see the NeurIPS code and data submission guidelines (https://nips.cc/public/guides/CodeSubmissionPolicy) for more details.
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   - The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (https://nips.cc/public/guides/CodeSubmissionPolicy) for more details.
   - The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
   - The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
   - 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.

6. **Experimental setting/details**

   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: The most important hyperparameter for running the experiments is the temperature setting in the models, which is provided in the appendix. Please note that due to the inherent randomness of some models, such as OpenAI's o3, it is not possible to fully reproduce their outputs.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
   - The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment statistical significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [No] .

   Justification: Most experiments in this paper were conducted using a temperature setting of zero, which generally produces consistent results across runs. However, some variation may still occur in specific reasoning models due to their inherent stochasticity. Nonetheless, the primary contribution of this work is the introduction of the dataset.

   Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments compute resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [NA]

   Justification: We utilize online inference providers to run the models.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code of ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics https://neurips.cc/public/EthicsGuidelines?

   Answer: [Yes]

   Justification: Our study does not involve human subjects, and all data was collected from publicly available sources.

   Guidelines:

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   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [NA] .

Justification: In this paper, we introduce a dataset for evaluating the capabilities of vision-language models (VLMs) in the context of video game quality assurance. There is no direct societal impact associated with our study. Although one may argue that our work could have implications for the labor market, we are not developing any models in this study that are intended to impact society in any way.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: In this paper, we introduce a dataset for evaluating the capabilities of vision-language models (VLMs) in the context of video game quality assurance. Safeguard measurements are not applicable to our study.

Guidelines:

- The answer NA means that the paper poses no such risks.
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Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: Please see Tab. A14.

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- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
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- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [Yes]

    Justification: We used Unity to generate several tasks in our dataset. While we provide as many details as possible in the main text, we are not releasing the raw 3D asset files or Unity project files due to ownership restrictions. However, we do release the final images and videos for each task.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: Our study does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: Our study does not involve human subjects.

Guidelines:

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- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
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16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: We used LLMs in various parts of this study. Most notably, the Gemini-2.5-Pro model was used to draft questions for subsets of the tasks in the dataset, as explained in the main text. Additionally, we used o3 to summarize a large volume of model-generated text in order to identify common patterns in a small subset of the study. None of these use cases involve non-standard components or constitute part of the core research methodology.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
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Appendix for: VideoGameQA-Bench: Evaluating Vision-Language Models for Video Game Quality Assurance

A Inference Providers

This section provides details about the inference providers and the inference settings used to run the benchmark.

Table A1: Inference configurations for open source models. All inference providers are enforced during testing.

Model Name	Temperature	Inference Provider	Platform
Llama-4-Maverick	0.0	Fireworks, Groq	OpenRouter, Groq
Llama-4-Scout	0.0	Fireworks, Groq	OpenRouter, Groq
Gemma-3	0.0	Novita, Nebius	OpenRouter
Mistral-Small-3.1 (24B)	0.0	Mistral, Nebius	OpenRouter
Qwen-2.5-VL (72B)	0.0	Novita	OpenRouter, AlibabaCloud

Table A2: Reasoning effort and thinking budget for tested models

Model Name	Reasoning Effort	Thinking Budget
o3	Medium	–
o4-mini	Medium	–
Gemini-2.5-Flash	–	0 (default)
Sonnet-3.7	–	0 (disabled)

Table A3: Frame sample rate for prompting LLMs with videos. While we typically use a sampling rate of one frame per second for all proprietary models, we lower this rate for open-source models to ensure that both the models and inference providers can handle the volume of images.

Model Name	Sampling rate
GPT-4.1	1 frame per second
GPT-4.1-mini	1 frame per second
GPT-4.1-nano	1 frame per second
GPT-4o	1 frame per second
o4-mini	1 frame per second
o3	1 frame per second
Gemini-2.5-Pro	1 frame per second
Gemini-2.5-Flash	1 frame per second
Gemini-2.0-Flash	1 frame per second
Sonnet-3.7	1 frame per second
Sonnet-3.5	1 frame per second
Llama-4-Scout	5 frames per video
Llama-4-Maverick	5 frames per video
Qwen-2.5-VL	10 frames per video
Mistral-Small-3.1	5 frames per video
Gemma-3	5 frames per video

Table A4: Exact model string version used in the evaluation.

Model Name	Version
GPT-4.1	gpt-4.1-2025-04-14
GPT-4.1-mini	gpt-4.1-mini-2025-04-14
GPT-4.1-nano	gpt-4.1-nano-2025-04-14
GPT-4o	gpt-4o-2024-08-06
o4-mini	o4-mini-2025-04-16
o3	o3-2025-04-16
Gemini-2.5-Pro	gemini-2.5-pro-preview-03-25
Gemini-2.5-Flash	gemini-2.5-flash-preview-04-17
Gemini-2.0-Flash	gemini-2.0-flash
Sonnet-3.7	claude-3-7-sonnet-20250219
Sonnet-3.5	claude-3-5-sonnet-20241022
Llama-4-Scout	meta-llama/llama-4-scout
Llama-4-Maverick	meta-llama/llama-4-maverick
Qwen-2.5-VL	qwen/qwen2.5-vl-72b-instruct
Mistral-Small-3.1	mistralai/mistral-small-3.1-24b-instruct
Gemma-3	google/gemma-3-27b-it

B Question Generation Prompts

Prompt for generating visual unit tests

```
You are an expert at generating visual unit test questions for
    images. Your task is to create precise questions that verify
    specific visual details in images, functioning as programmatic
    tests to confirm the presence, position, and attributes of
    characters and scene elements.

For each question you generate:
1. Focus on one specific testable visual element
2. Be extremely precise about the attribute being verified
3. Provide a JSON template with appropriate fields that could be
    used in automated testing
4. Use boolean values, counts, or enumerated options where possible
     for objective verification

VISUAL UNIT TEST FOCUS AREAS:

CHARACTER DETAILS:
- Facial features (eyes open/closed, mouth expression, gaze
    direction)
- Hand positions (gestures, holding objects, contact with other
    elements)
- Body posture (standing, sitting, leaning, specific pose)
- Clothing details (colors, patterns, state of clothing)
- Character positioning relative to scene or other characters

SCENE ELEMENTS:
- Object presence and count (specific items in the scene)
- Spatial relationships (left/right/above/below relationships
    between elements)
- Background details (setting type, time of day, weather indicators
    )
- Text elements (signs, labels, readable text)
- Visual states of objects (open/closed, on/off, intact/broken)

SAMPLE UNIT TEST QUESTIONS:

Example 1:
Is the character's right hand making contact with any object in the
     scene? If yes, identify which object.

Provide your answer in the following JSON format:
{
  "right_hand_contact_with_object": false,
  "contacted_object": "",
  "grip_type": "",
  "fingers_visible": 0
}
```

Figure A1: We use Gemini-2.5-Pro to draft an initial visual unit test based on an existing image.

Prompt for generating UI/OCR related questions

```
You are an expert at analyzing user interfaces, heads-up displays (
    HUDs), and text content in images. Your task is to create
    questions that verify visual UI/HUD elements and text content (
    OCR) in screenshots or images containing digital interfaces.

For each question you generate:
1. Focus on specific UI elements, layout, text content, or status
    indicators
2. Create a precise question that can be objectively verified
3. Provide a JSON template with appropriate fields for the
    structured response
4. Include placeholder values (zeros, empty strings, false) in the
    JSON template

QUESTION CATEGORIES TO INCLUDE:
- Text verification (e.g., "What text appears in the header/button/
    notification?")
- Element presence (e.g., "Which menu options are visible in the
    navigation bar?")
- UI state verification (e.g., "Is the toggle switch in the ON or
    OFF position?")
- Color and styling (e.g., "What color is the error message
    displayed?")
- Layout confirmation (e.g., "Is the search bar located at the top
    or bottom of the interface?")
- Icon identification (e.g., "Which notification icons are present
    in the status bar?")
- Element counting (e.g., "How many form fields are visible on this
     page?")
- Status indicators (e.g., "What is the battery percentage shown?")

EXAMPLE QUESTIONS WITH JSON TEMPLATES:

Example 1:
What text is displayed in the error message dialog box, and what
    button options are available?

Provide your answer in the following JSON format:
{
  "error_message_text": "",
  "button_options": [],
  "is_dismissible": false,
  "dialog_color": ""
}
```

Figure A2: We use Gemini-2.5-Pro to draft an initial UI unit test based on an existing image.

C Prompt design and variation experiments

We adopted a lightweight meta-prompting workflow to design all prompts used in the experiments. We first provided a clear task description and several candidate prompts generated by Sonnet-3.7, followed by a brief editorial pass by one author to ensure clarity and consistency. The same task prompts were then applied across all models.

Prompt variation experiments. To assess sensitivity to phrasing, we further used Sonnet-3.7 to generate ten alternative prompts for the image-based glitch detection and bug-report generation tasks. We then ran the full experiment on GPT-4.1 and computed mean accuracy, standard deviation, and range across variants (see Table A5).

Table A5: Prompt variation experiment results for image-based glitch detection tasks

Task	Model	Mean Acc. (%)	Std. (%)	Min (%)	Max (%)	# Variants
Image Glitch Detection	GPT-4.1	80.12	3.25	73.80	83.60	10
Image Bug Report Generation	GPT-4.1	50.7	2.58	46.0	54.0	10

For image glitch detection, the mean accuracy (80.1%) was slightly below the main reported result (81.3%), while the highest variant reached 83.6%, a 2.3-point improvement over the base prompt. For bug-report generation, the mean accuracy (50.7%) was marginally lower than the base result (51.0%), with the best variant reaching 54.0%. Overall, these findings suggest that prompt wording can shift scores by only a few points and does not alter the overall comparative conclusions.

All prompts are provided in the subsequent section Appendix D.

D Model Inference Prompts

Prompt for Glitch Detection (Image)

```
You are a helpful assistant analyzing video game images and
    screenshots for glitches. You will be given a screenshot from a
    video game, and your job is to analyze the screenshot and
    determine whether it contains a glitch.

Provide your answer in the following format:

{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A3: The default prompt associated with each image in the dataset for the image-based glitch detection task.

Prompt for Glitch Detection (Video)

```
You are a helpful assistant analyzing video game clips for glitches
    . You will be given a short video clip from a video game, and
    your task is to analyze the video and determine whether it
    contains a glitch.

Provide your answer in the following format:

{
  "reasoning": "Brief explanation of why you think a glitch is
    present or not",
  "glitch_detected": true or false,
  "description_of_glitch": "Description of the glitch if detected,
    otherwise leave this blank"
}
```

Figure A4: The default prompt associated with each image in the dataset for the video-based glitch detection task.

Prompt for Generating Bug Reports (Image)

```
You are a video game quality assurance assistant who analyzes
    screenshots to identify and document visual glitches. When
    presented with an image, carefully examine it for any graphical
    bugs or rendering issues.

Provide your analysis in the following JSON format:

{
    "reasoning": "Brief explanation of what you observe and why it
    appears to be a glitch",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug, including its appearance and potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI) affected by the glitch"
}
```

Figure A5: The default prompt used for generating bug reports based on a given image.

Prompt for Generating Bug Reports (Video)

```
You are a video game quality assurance assistant who analyzes video
     clips to identify and document visual glitches or strange
    behaviors. When presented with a video clip, carefully examine
    it for any graphical bugs, rendering issues, physics anomalies,
    or unexpected events.

Provide your analysis in the following JSON format:

{
    "reasoning": "Brief explanation of what you observe in the
    video and why it appears to be a glitch or bug",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug or behavioral anomaly, including its appearance and
    potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI, physics) affected by the glitch"
}
```

Figure A6: The default prompt used for generating bug reports based on a given video.

Prompt for Visual Regression Task

```
You are an image comparison tool for video game quality assurance.
    Given two screenshots from the same game scene, evaluate whether
     the second image represents an acceptable variation of the
    first (reference) image.

Consider these variations ACCEPTABLE:
- Player character customization elements
- Environmental conditions (weather, day/night cycle)
- Slight positional or animation differences
- Lighting and shadow adjustments
- Minor variations in non-critical background elements

Consider these variations UNACCEPTABLE:
- Interface corruption or element misalignment
- Textual content changes (unless expected, e.g., dynamic text)
- Significant visual artifacts or rendering errors (e.g., missing
    textures, z-fighting)
- Major structural changes to scene geometry not attributable to
    gameplay state
- Missing or grossly incorrect key scene elements compared to the
    reference

Provide your assessment as JSON:
{
  "reasoning": "Concise explanation of detected differences and
    justification for your decision based on the criteria.",
  "test_pass": true/false
}
```

Figure A7: A sample prompt used in the visual regression task to detect changes between two versions of the same scene. Depending on the complexity and source of the scene—whether generated in Unity or extracted from a YouTube video—the items listed under acceptable and unacceptable categories vary.

Prompt for Detecting Clipping (Parametric Test)

```
You are a visual analysis assistant specializing in detecting
    object clipping in video game screenshots. Your task is to
    examine each provided image and determine whether any part of
    the white cube is intersecting with the character model,
    indicating a clipping issue.

Based on your analysis, respond using the following format:

{
    "reasoning": "Brief explanation of why you think clipping is
    present or not",
    "clipping_detected": true or false
}
```

Figure A8: The default prompt used for parametric tests to detect object clipping at various proximities.

Prompt for Needle In a Haystack

````
You are a specialized video game quality assurance analyst trained
    to detect visual anomalies in gameplay footage. Your task is to
    analyze the provided video clip to identify any bugs, glitches,
    visual artifacts, or unexpected behaviors.

## What to Look For

Examine the video carefully for any:

- Visual artifacts (texture issues, flickering, clipping)
- Animation problems (jerky movements, T-poses)
- Rendering glitches (missing textures, lighting errors)
- Gameplay anomalies (collision failures, object teleportation)

## Response Format
After your thorough analysis, provide your findings in this exact
    JSON format:

```json
{
  "reasoning": "Brief explanation of what you observed in the video
     and why it appears to be a glitch",
  "glitch_detected": true|false,
  "timestamp": 0
}
```
````

Figure A9: The default prompt used for Needle In a Haystack tests to detect and locate glitches in a video clips

E LLM-as-a-Judge

Developer Prompt Message for Evaluating Bug Reports

```
You are a quality assurance verification assistant that evaluates
    bug reports against known issues. When provided with both a
    generated bug report and a ground truth description, your task
    is to determine if they describe the same bug.

Compare the generated bug report with the ground truth description
    carefully. Focus on whether they identify the same core issue,
    even if expressed differently.

Respond *only* with the following JSON format:

{
    "reasoning": "Detailed explanation of why the bug report does
    or does not match the ground truth description, highlighting
    specific similarities or differences",
    "match": true or false
}
```

Figure A10: A sample developer message used with o3 to judge the accuracy of a bug report given a ground truth label.

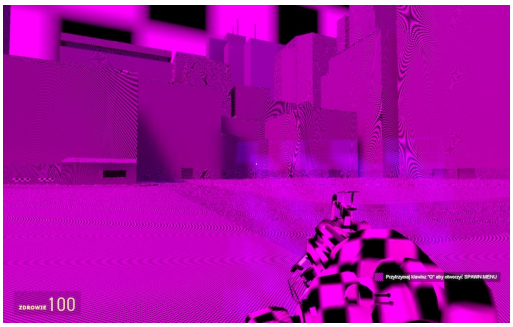
Developer Prompt Message for Evaluating Bug Reports

```
You are a quality assurance verification assistant that evaluates
    bug reports against known issues. Your task is to determine if a
     generated bug report and a ground truth description refer to
    the same underlying bug.

When comparing:
- Focus on the core issue or behavior rather than exact wording
- Consider if they describe the same symptoms, affected features,
    and conditions
- A match exists even if details like error messages or steps
    differ slightly
- Pay attention to technical specifics that distinguish similar-
    looking bugs

Two descriptions may use different terminology but still describe
    the same bug. Conversely, reports with similar symptoms might
    describe different bugs if they have different root causes.

Your final response should be a JSON object with the following
    format:

{
    "reasoning": "Detailed explanation of why the bug report does
    or does not match the ground truth description, highlighting
    specific similarities or differences",
    "match": true or false
}
```

Figure A11: A sample developer message used with o3 to judge the accuracy of a video-based bug report generation task, given a ground truth label.

F Samples for different glitch types

F.1 Missing or corrupted assets/textures

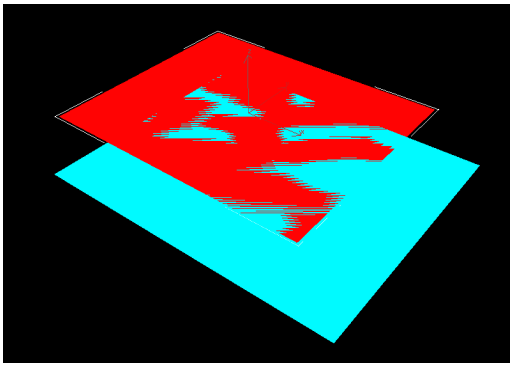


(a)

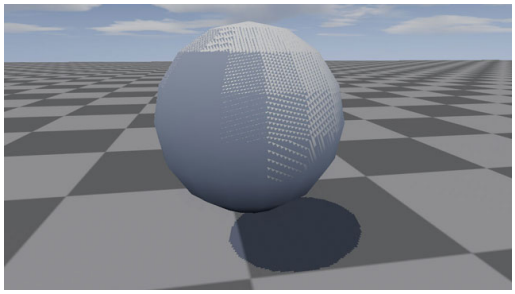
(b)

Figure A12: Examples of missing or corrupted textures. Sources: (a), (b).

F.2 Geometry and rasterization issues



(a)



(b)

Figure A13: Examples of geometry and rasterization issues (z-fighting and shadow acne). Sources: (a), (b).

F.3 Temporal instability

(a)

(b)

Figure A14: Examples of temporal instability. 3D meshes start to appear slowly in the game with a noticeable delay. Please watch the video for more details.

F.4 Post-processing and UI artifacts

(a) (b)

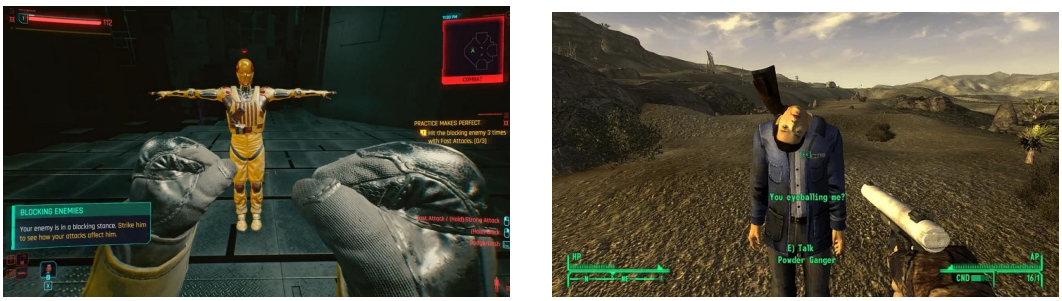
Figure A15: Examples of post-processing and UI artifacts. Sources: (a), (b).

F.5 Physics and collision failures

(a) (b)

Figure A16: Examples of physics and collision failures. Sources: (a), (b).

F.6 Animation/state errors

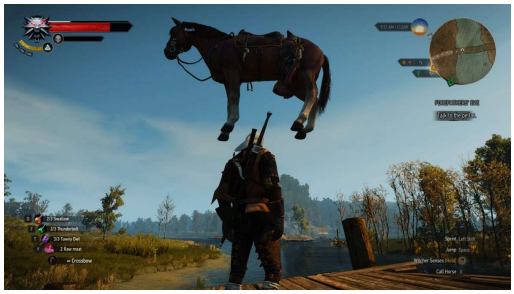


(a) (b)

Figure A17: Examples of animation/state errors. Sources: (a), (b).

F.7 World and rule violations

(a)

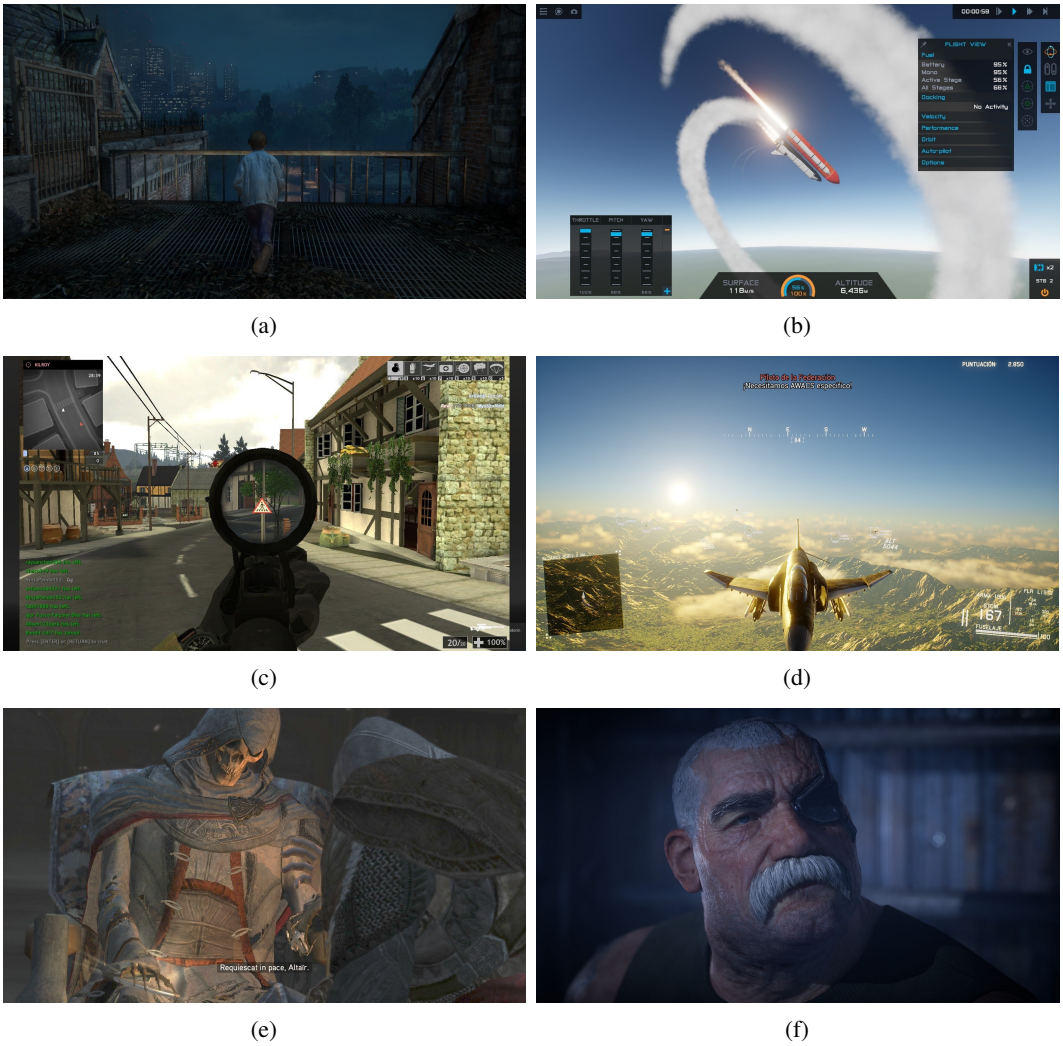


(b)

Figure A18: Examples of world and rule violations. Sources: (a), (b).

G Additional Results

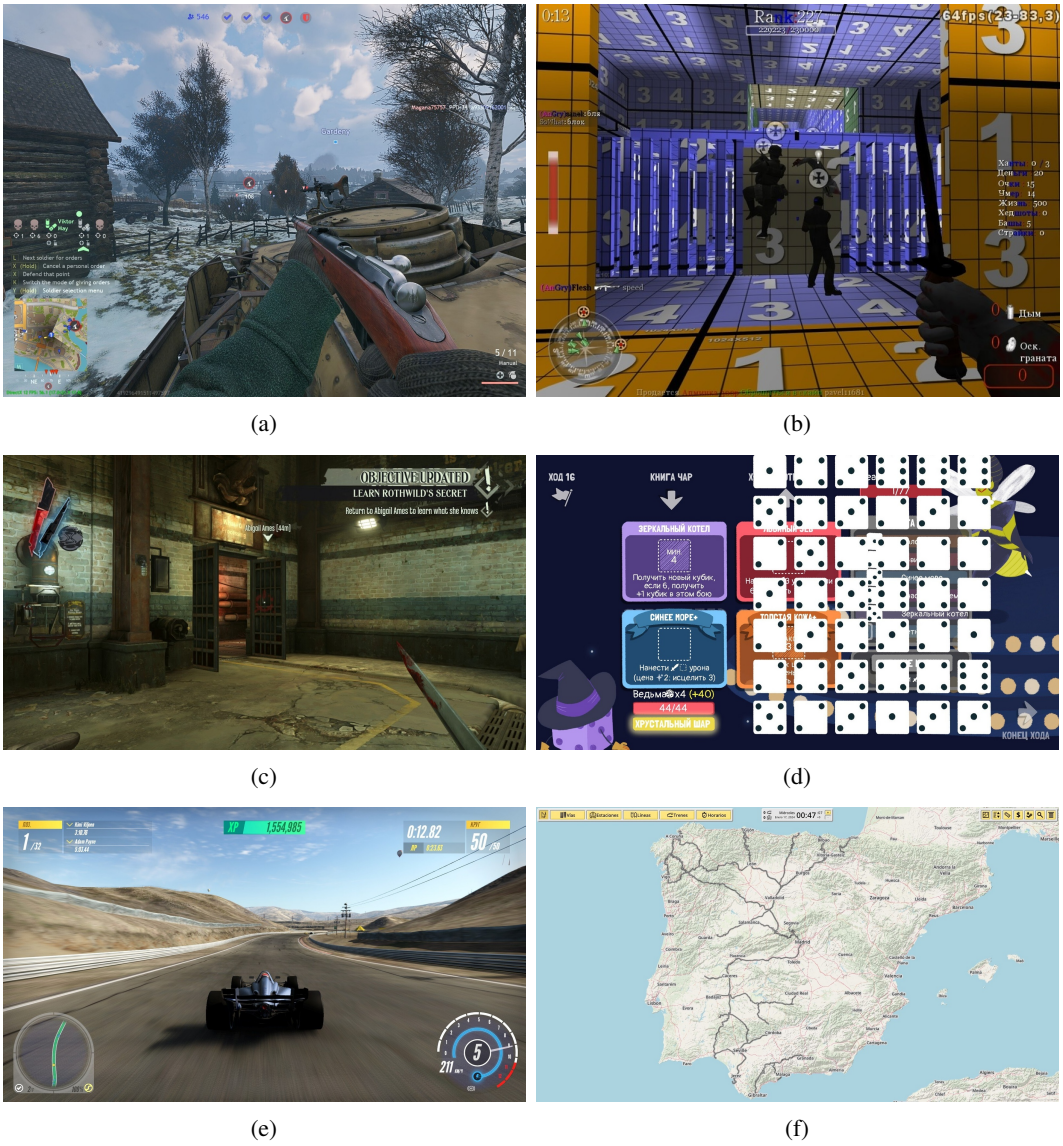
G.1 Additional Results for the Visual Unit Testing Task



(a) (b) (c) (d) (e) (f)

Figure A19: Common failures among tested models for visual unit testing include: (a) models struggling to accurately report the character's posture, direction, time of day, and other scene details; (b) models struggling to report whether the shuttle orientation is upward or downward; (c) models failing to report whether the door on the right is open or closed; (d) models failing to detect whether the orientation of the aircraft is facing toward or away from the camera; (e) models failing to notice small details on characters' clothing; and (f) models failing to describe the facial hair of the character.

G.2 Additional Results for the UI Unit Testing Task



(a) (b)

(c) (d)

(e) (f)

Figure A20: Common failures among the tested models for UI unit testing include: (a) models failing to read UI elements at the top of the image to calculate the number of objectives captured and the remaining objectives; (b) models failing to recognize all textual elements in the scene, including the exact positions of numbers on the orange and blue tiles; (c) models failing to recognize the current values of various customized progress bars; (d) models failing to read information from grids, such as tile pieces, dice numbers, or configurations of game boards; (e) models struggling to read speedometer values and extract positional information from maps; (f) models failing to extract positional information from maps and determine relationships between specific nodes.

G.3 Model refusal rates and malformed JSON

Tab. A6 shows unified *parse-error rate* that combines two related failure modes: (i) the model generates syntactically invalid JSON, or (ii) it refuses to produce an answer. We unify both malformed outputs and refusals under a single parse-error rate metric because both prevent downstream scoring.

Overall, error rates are low and confirm that requiring JSON structure does not meaningfully reduce task performance. For most models, parse errors remain below 3%, primarily arising from minor bracket or quotation mismatches in UI/unit-test tasks. The only notable outlier is Gemma-3, which shows an 8.7% error rate in image-based glitch detection task; however, manual inspection reveals that nearly all cases correspond to refusals (*I cannot help with that*) rather than true syntax failures. Among video-based tasks, Sonnet-3.5 and GPT-4.1 exhibit elevated refusal rates (14% and 28%, respectively) on longer clips, reflecting temporary refusal triggers rather than structural decoding issues.

In summary, structured output compliance remains robust across all tasks, and parsing errors are dominated by refusals rather than syntax, indicating that enforcing a JSON schema is a safe and informative diagnostic rather than a limiting factor.

Table A6: Parse-error rates (%) caused by models producing malformed JSON or refusing to answer. Overall error rates are low, confirming that enforcing a JSON schema does not itself reduce task performance. GPT-4.1 exhibits the highest error rate on video-based tasks, primarily due to refusals to answer.

	Image					Video	
	VU	UI	VR	IGD	PCD	VGD	NIAH
Model / # Samples	100	100	250	1000	686	1000	100
GPT-4.1	0.0	0.00	0.00	0.00	0.0	0.00	4.00
GPT-4.1-mini	0.0	0.00	0.00	0.10	0.0	0.00	0.00
GPT-4.1-nano	0.0	1.00	0.00	0.00	0.0	0.00	0.00
GPT-4o	0.0	1.00	0.00	0.10	0.0	28.20	93.00
o4-mini	0.0	4.00	0.00	0.00	0.0	0.20	0.00
o3	0.0	1.00	0.00	0.00	0.0	0.00	0.00
Gemini-2.5-Pro	0.0	1.00	0.00	0.00	0.0	0.00	0.00
Gemini-2.5-Flash	0.0	1.00	0.00	0.00	0.0	0.00	0.00
Gemini-2.0-Flash	0.0	0.00	0.00	0.00	0.0	0.00	0.00
Sonnet-3.7	0.0	0.00	0.80	0.00	0.0	0.40	0.00
Sonnet-3.5	0.0	0.00	0.00	0.10	0.0	14.00	1.00
Llama-4-Scout	4.00	2.00	0.00	0.10	0.14	4.00	–
Llama-4-Maverick	4.00	1.00	0.00	0.10	0.58	5.30	–
Gemma-3 (27B)	2.00	0.00	0.00	8.70	0.00	0.20	–
Mistral-Small-3.1 (24B)	0.00	0.00	0.00	0.00	0.00	3.60	–
Qwen-2.5-VL (72B)	0.00	2.00	0.80	0.20	0.00	13.10	–

G.4 Additional Performance Metrics for the Glitch Detection Tasks

In this section, we provide performance metrics for different models. The total number of test cases in both image- and video-based glitch detection is 1,000. The # samples column is not always 1,000 because some models either generated invalid JSON or refused to provide a valid answer to the given question for various reasons.

Table A7: Performance metrics for different models on the **image-based** glitch detection task. Metrics include Accuracy (Acc), True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), Precision (Prec), Recall (Rec), F1 Score (F1), and Specificity (Spec).

Model	Acc.	TP	FP	FN	TN	Prec.	Rec.	F1	Spec.	# *Samples*
GPT-4.1	81.3	374	61	126	439	86.0	74.8	80.0	87.8	1,000
GPT-4o-mini	76.9	468	199	32	300	70.2	93.6	80.2	60.1	999
GPT-4.1-nano	57.0	413	343	87	157	54.6	82.6	65.8	31.4	1,000
GPT-4o	82.9	417	89	82	411	82.4	83.6	83.0	82.2	999
o4-mini	76.4	331	67	169	433	83.2	66.2	73.7	86.6	1,000
o3	73.7	253	16	247	484	94.1	50.6	65.8	96.8	1,000
Gemini-2.5-Pro	75.5	418	164	81	336	71.8	83.8	77.3	67.2	999
Gemini-2.5-Flash	66.4	215	52	284	448	80.5	43.1	56.1	89.6	999
Gemini-2.0-Flash	68.1	259	78	241	422	76.9	51.8	61.9	84.4	1,000
Sonnet-3.7	65.1	177	26	323	474	87.2	35.4	50.4	94.8	1,000
Sonnet-3.5	70.2	238	37	261	463	86.5	47.7	61.5	92.6	999
Llama-4-Scout	55.9	74	16	425	484	82.2	14.8	25.1	96.8	999
Llama-4-Maverick	53.3	44	11	456	488	80.0	8.8	15.9	97.8	999
Gemma-3	51.2	460	446	0	7	50.8	100.0	67.3	1.5	913
Mistral-Small-3.1	59.7	230	133	270	367	63.4	46.0	53.3	73.4	1,000
Qwen-2.5-VL	70.1	254	52	246	446	83.0	50.8	63.0	89.6	998

Table A8: Performance metrics for different models on the **video-based** glitch detection task. Metrics include Accuracy (Acc), True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), Precision (Prec), Recall (Rec), F1 Score (F1), and Specificity (Spec).

Model	Acc.	TP	FP	FN	TN	Prec.	Rec.	F1	Spec.	# *Samples*
GPT-4.1	76.6	411	149	83	347	73.4	83.2	78.0	70.0	990
GPT-4o-mini	72.2	346	124	153	372	73.6	69.3	71.4	75.0	995
GPT-4.1-nano	49.9	466	468	24	25	49.9	95.1	65.5	5.1	983
GPT-4o	79.9	356	53	90	214	87.0	79.8	83.3	80.2	713
o4-mini	73.1	330	115	143	370	74.2	69.8	71.9	76.3	958
o3	77.2	298	27	200	470	91.7	59.8	72.4	94.6	995
Gemini-2.5-Pro	78.1	334	53	166	447	86.3	66.8	75.3	89.4	1,000
Gemini-2.5-Flash	64.7	426	279	74	221	60.4	85.2	70.7	44.2	1,000
Gemini-2.0-Flash	54.5	477	432	23	68	52.5	95.4	67.7	13.6	1,000
Sonnet-3.7	67.4	250	79	245	419	76.0	50.5	60.7	84.1	993
Sonnet-3.5	73.6	266	70	150	346	79.2	63.9	70.7	83.2	832
Llama-4-Scout	61.0	117	25	349	469	82.4	25.1	38.5	94.9	960
Llama-4-Maverick	59.8	82	6	375	484	93.2	17.9	30.1	98.8	947
Gemma-3	51.4	498	484	1	15	50.7	99.8	67.2	3.0	998
Mistral-Small-3.1	63.7	238	112	238	376	68.0	50.0	57.6	77.0	964
Qwen-2.5-VL	55.1	99	2	388	380	98.0	20.3	33.7	99.5	869

G.5 Is GPT-4o Ready to Be Deployed as an Autonomous Glitch-Detection System?

Given the observed test accuracy of 82.9% for GPT-4o in glitch detection task (with an equal number of glitch and glitch-free images), the natural question arises: *Is this performance sufficient for real-world autonomous deployment?* To address this question, it is important to consider the real-world scenario where glitches are relatively rare.

If we assume that a glitch appears in only 5% of normal gameplay sessions, this prevalence assumption significantly changes the performance characteristics. Specifically, the confusion matrix obtained from our controlled benchmark test (Tab. A7) translates poorly to real-world precision. Given the current model:

Deployment targets

- **Recall** $\geq 95\%$ on the balanced benchmark.
- **False-positive rate** $\leq 0.5\%$ ($\leq$ 2 FP in 500 normals).
- **Precision** $\geq 90\%$ when prevalence is 5%.
- **Balanced accuracy** $\geq 97\%$.

Balanced-benchmark performance of GPT-4o

From Tab. A7 (999 images, 499 glitch / 500 normal):

$$\begin{aligned} \text{TP} &= 417, \quad \text{FP} = 89, \\ \text{FN} &= 82, \quad \text{TN} = 411. \end{aligned}$$

- **Recall** $= 417/(417+82) = \mathbf{83.6}\%$ (11.4 pp below the 95% target).
- **False-positive rate** $= 89/(89+411) = \mathbf{17.8}\%$ ($35.6\times$ the allowable 0.5%).
- **Balanced accuracy** $= \frac{1}{2}(83.6+82.2) = \mathbf{82.9}\%$ (14.1 pp short of 97%).
- **Precision** $= 417/(417+89) = \mathbf{82.4}\%$.

Projected real-world performance (5% prevalence)

Let $p = 0.05$ be the real glitch rate and $\alpha = 17.8\%$ the measured FPR. With prevalence shift we obtain

$$\text{Precision}_{p=0.05} = \frac{p\,\text{Recall}}{p\,\text{Recall} + (1-p)\,\alpha} = \frac{0.05 \times 0.836}{0.05 \times 0.836 + 0.95 \times 0.178} = \mathbf{19.8}\%.$$

Interpretation: in live use, roughly ~ 5 alarms will be false for every true glitch detected.

Assessment: GPT-4o falls short of *all four* deployment targets:

Metric	Target	GPT-4o	Gap
Recall (balanced)	$\geq 95\%$	83.6%	-11.4 pp
False-positive rate	$\leq 0.5\%$	17.8%	$+17.3$ pp ($35.6\times$)
Precision (5%)	$\geq 90\%$	19.8%	-70.2 pp
Balanced accuracy	$\geq 97\%$	82.9%	-14.1 pp

Despite relativity high accuracy in balanced-benchmark, GPT-4o 's high false-positive rate dominates under real-world class imbalance, crushing precision to $\sim 20\%$.

Conclusion: GPT-4o, in its present configuration, is *not yet ready* for *standalone autonomous* bug detection. Substantial improvements in both sensitivity (recall) and specificity (false–positive control) are required before deployment can be considered.

G.6 Common False Positive Patterns, as Summarized by o3

Prompt for Summarizing False Positive Cases

```
Analyze false positive cases from the glitch detection system to
    identify recurring patterns. Create a structured summary that:

1. Lists the 3-5 most common false positive types
2. Notes frequency and severity patterns

Keep your summary under 500 words with clear, actionable insights.
```

Figure A21: The prompt used with o3 to read the reasoning fields for false positive cases from top models and summarize their common patterns.

Table A9: Recurring false–positive themes in GPT-4.1's output ($N = 61$).

Rank	False-positive type	Frequency	Severity†	Typical trigger / pattern
1	Model / prop clipping & intersection	27 (44%)	Low–Moderate	Mesh overlap flagged even when brief or hidden behind UI.
2	Missing / distorted textures & artifacts	14 (23%)	Moderate	Large placeholder colours or high-contrast patterns; mis-classifies VFX/debug overlays.
3	Floating / mis-aligned actors or objects	12 (20%)	Low	Height checks too strict; intentional offsets on uneven terrain reported.
4	UI / text-render issues	9 (15%)	Low–Moderate	Any mismatch between world and HUD layers (overlays, mods) triggers alert.

†Severity gauges player impact: cosmetic (low) to gameplay-blocking (high).

Table A10: Recurring false–positive themes in GPT-4o's output ($N = 90$).

Rank	False-positive type	Frequency	Severity†	Typical trigger / pattern
1	Floating / unsupported entities	$\sim 40\%$	Moderate	Characters, vehicles or scenery hovering above terrain or water
2	Clipping & collision overlaps	$\sim 30\%$	Moderate–High	Limbs, weapons or duplicate models intersecting geometry or each other
3	Missing / placeholder textures	$\sim 15\%$	High	Bright-pink or solid-blue fallback materials, transparent/missing walls
4	UI / text anomalies	$\sim 10\%$	Low	HUD layers visible through world, "????" strings, overlapping menus
5	Model / texture distortions	$\sim 5\%$	Medium	Elongated limbs/necks, stretched terrain, unnatural global color tints

†Severity is qualitative and reflects typical impact on gameplay and QA triage effort.

Table A11: Recurring false–positive themes in Gemini-2.5-Pro's output ($N = 165$).

Rank	False-positive type	Frequency	Severity[†]	Typical trigger / pattern
1	Model clipping / interpenetration	27 (44%)	Low–Medium	Limbs, weapons, or vehicles intersecting terrain or other meshes; descriptions using "clipping", "inside", "passing through".
2	UI & text-layout errors	15 (25%)	Low–Medium	Overlapping chat/tooltips, truncated strings, cursor or debug labels drawn on wrong layer.
3	Physics / collision anomalies	9 (15%)	Medium	Floating characters or props, impossible resting angles, ragdolls stuck in geometry.
4	Numerical or logical inconsistencies	6 (10%)	Medium	Impossible values (e.g. 100.58% accuracy, "00:16:65" timers, "+0 points $\rightarrow$ promotion").
5	Rendering / texture artifacts	3 (5%)	Low	Rainbow shaders, corrupted textures, overbloom or missing materials visible only on surfaces.

[†]Severity ranks the typical gameplay impact: *Low* = cosmetic, *Medium* = may mislead or soft-lock, *High* = blocks progress or crashes.

G.7 Additional Results for the Glitch Detection Task

GPT-4o's output:

```
{
    "reasoning": "The vehicle is floating above the trees, which is
     not typical behavior in the game.",
    "glitch_detected": true,
    "description_of_glitch": "A vehicle is floating in mid-air
    above the trees."
}
```

o4-mini's output:

```
{
  "reasoning": "There's an unexpected blank white bar at the bottom
     of the HUD where game info (such as health or status) should be
     rendered, indicating a missing or corrupted UI texture.",
  "glitch_detected": true,
  "description_of_glitch": "A plain white rectangle is displayed at
     the bottom center of the screen instead of the normal HUD
    element, suggesting a UI texture failed to load or render
    properly."
}
```

GPT-4.1's output:

```
{
  "reasoning": "The vehicle visible through the scope appears to be
     floating above the trees, which is not typical behavior for
    vehicles in the game. Normally, vehicles should be on the ground
    , not suspended in mid-air.",
  "glitch_detected": true,
  "description_of_glitch": "A vehicle is floating above the trees,
    indicating a physics or rendering glitch where the vehicle is
    not interacting with the terrain as expected."
}
```

Figure A22: Sample successful glitch detections by various models that identified the floating vehicle.

Gemini-2.5-Pro's output:

```
{
    "reasoning": "The player character appears to be holding both a
     knife and a pistol simultaneously in a way that suggests a
    visual glitch. The knife model seems to be superimposed or
    clipping through the hand that is holding the pistol. In most
    first-person games, including Payday 2 (which this game appears
    to be), players switch between melee and ranged weapons rather
    than wielding them concurrently in this manner.",
    "glitch_detected": true,
    "description_of_glitch": "The character model is incorrectly
    displaying both a melee weapon (knife) and a firearm (pistol) as
     actively wielded at the same time, with the knife model
    appearing to clip through or be superimposed on the hand holding
     the pistol."
}
```

Qwen-2.5-VL's output:

```
{
    "reasoning": "The screenshot shows a player holding both a
    knife and a gun simultaneously, which is not typical in most
    games where players can only wield one weapon at a time. This
    suggests a potential glitch in the game's weapon handling system
    .",
    "glitch_detected": true,
    "description_of_glitch": "The player is holding a knife and a
    gun at the same time, which is not a standard feature in the
    game and indicates a glitch in the weapon system."
}
```

GPT-4.1-mini's output:

```
{
    "reasoning": "The knife held by the character is unusually
    large and appears to be clipping through the hand, which is not
    typical for the game's weapon models. This suggests a graphical
    or model scaling glitch.",
    "glitch_detected": true,
    "description_of_glitch": "The knife model is abnormally large
    and clips through the character's hand, indicating a weapon
    model scaling or rendering glitch."
}
```

Figure A23: Sample successful glitch detections by various models that identified a clipping knife overlapping with a gun.

Llama-4-Maverick's output:

```
{
    "reasoning": "The screenshot appears to be a scene from a video
     game where a police officer is standing in the middle of a road
     with an ambulance and a police car nearby. The image does not
    show any obvious graphical distortions, texture issues, or
    abnormal behavior that would typically be associated with
    glitches. The scene looks like it is part of the game's intended
     content, with the character and vehicles positioned in a
    plausible scenario. The text at the bottom of the screen
    suggests a narrative or dialogue element, further indicating it
    is part of the game's story or interaction.",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

Gemini-2.0-Flash's output:

```
{
    "reasoning": "Based on the image, there is no indication of any
     glitches. The graphics appear normal, and there are no visual
    artifacts or anomalies that would suggest a problem with the
    game's rendering or programming.",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

Sonnet-3.7's output:

```
{
    "reasoning": "The screenshot appears to show normal gameplay
    from what seems to be a police or emergency services simulation
    game. The scene shows a character in a police uniform standing
    on a street with an ambulance and police vehicle parked nearby.
    The UI elements, including mission text (in what appears to be
    Chinese characters), progress bars, and resource counters are
    all displaying normally. The vehicles and environment are
    rendering as expected without any visual artifacts, texture
    issues, or clipping problems.",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

Figure A24: Sample image where models failed to detect a clipping glitch between two cars.

o4-mini's output:

```
{
    "reasoning": "One of the soldiers on the left is clipping
    through the lower bunk rather than standing or climbing normally
    , and their arms and torso intersect the bed mesh in an
    unnatural way.",
    "glitch_detected": true,
    "description_of_glitch": "Character model is stuck in the bunk
    bed, clipping through the mattress and frame instead of
    animating a proper climb or stand."
}
```

Gemini-2.5-Pro's output:

```
{
    "reasoning": "The character on the bottom left bunk bed has
    their legs and lower torso clipping through the mattress and bed
     frame, which is a common visual glitch.",
    "glitch_detected": true,
    "description_of_glitch": "A character's lower body is clipping
    through a bed. Specifically, the character on the bottom left
    bunk bed has their legs and lower torso passing through the
    mattress and bed frame."
}
```

Sonnet-3.5's output:

```
{
    "reasoning": "The image shows characters clipping through/
    intersecting with hospital beds, which is not physically
    possible and appears to be a collision detection issue",
    "glitch_detected": true,
    "description_of_glitch": "Character models are clipping through
     the hospital beds instead of lying properly on top of them.
    This appears to be happening with multiple characters in the
    scene, suggesting a collision detection or character positioning
     glitch."
}
```

Figure A25: Sample image where various models incorrectly reported the presence of a glitch, although the image is glitch-free.

Llama-4-Scout's output:

```
{
    "reasoning": "The image appears to be a normal in-game
    screenshot from MotoGP24, showing a motorcycle race with a rider
     on a track. There are no obvious visual artifacts, clipping
    issues, or other graphical anomalies that would indicate a
    glitch. The scene is consistent with what is expected in a
    racing game.",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

o4-mini's output:

```
{
    "reasoning": "The scene shows a well-rendered MotoGP bike
    leaning on the track with proper textures, lighting, and depth-
    of-field. There are no visible clipping issues, missing textures
    , or geometry errors.",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

Qwen-2.5-VL's output:

```
{
    "reasoning": "The image appears to be a normal scene from the
    game MotoGP 24, showing a motorcycle racer on a track with a
    large bull statue in the background. There are no visible
    anomalies or unexpected behaviors that would indicate a glitch
    .",
    "glitch_detected": false,
    "description_of_glitch": ""
}
```

Figure A26: Sample image where various models correctly reported the image as glitch-free.

G.8 Sample False Positive and False Negative Cases in the Image-based Glitch Detection Task that Most Models Labeled Incorrectly

In this section, we provide sample images from common false positive and false negative cases, where most models are confused about the correct label of the image.

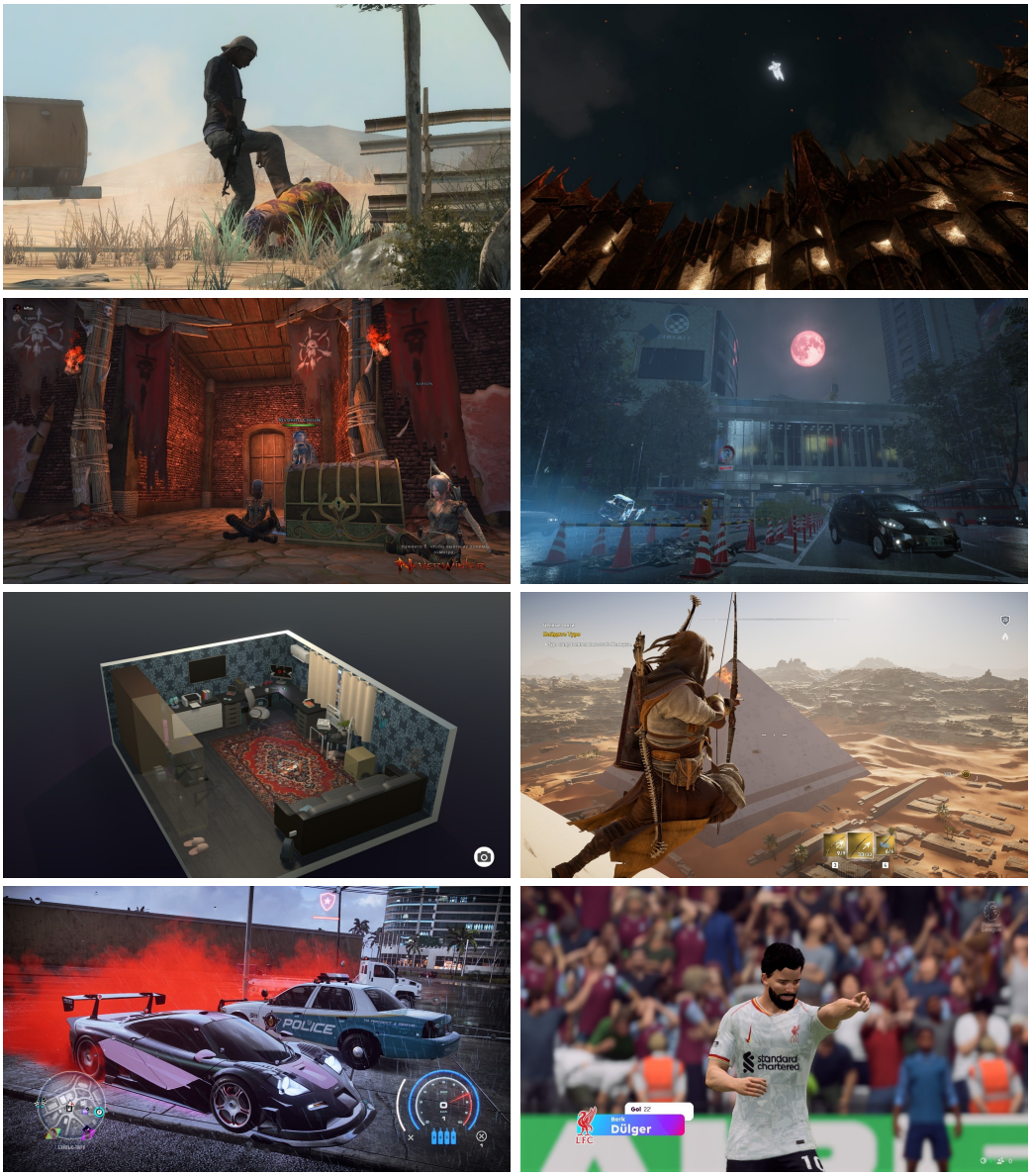


Figure A27: Sample images from image-based glitch detection, where models reported the image as glitchy despite it being glitch-free (false positive).

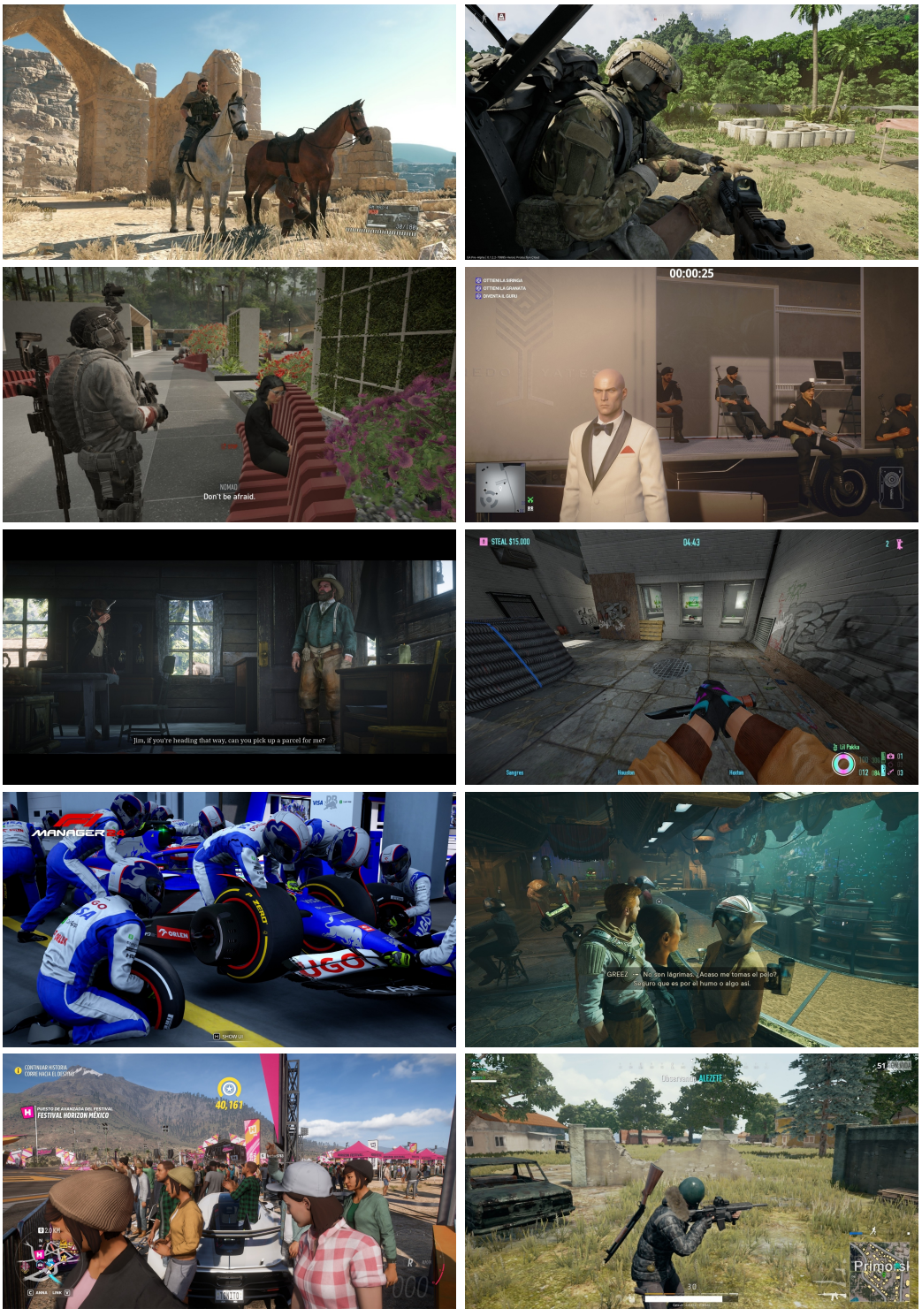


Figure A28: Sample images from image-based glitch detection, where the majority of models failed to detect the glitch in the image (false negative).

G.9 Additional Results for the Video-based Glitch Detection Task

GPT-4.1's output:


```
{
  "reasoning": "In the sequence of images, the player character's
    model appears to be severely distorted, particularly around the
    torso and back area, which is unnaturally enlarged and misshapen
    . This is not consistent with normal character models in video
    games and suggests a graphical or animation glitch affecting the
     character's mesh or skeleton.",
  "glitch_detected": true,
  "description_of_glitch": "The player character's body is
    unnaturally deformed, with an exaggerated and misshapen torso
    and back, indicating a character model or animation glitch."
}
```


Gemini-2.0-Flash's output:


```
{"description_of_glitch": "The character's back is unnaturally
    deformed, suggesting a glitch in the character model or
    animation.", "glitch_detected": true, "reasoning": "The
    character's back appears to have a large, unnatural bulge, which
     is not typical of human anatomy and suggests a graphical or
    animation error."}
```


Figure A29: Sample from a video-based glitch detection task in which various models correctly identified a glitch related to the character's body.

o3's output:

```
{
  "reasoning": "After the skater bails, the board no longer behaves
     normally. It repeatedly clips halfway into the sidewalk,
    jitters and spins in place, and even drifts around on its own
    while the player simply stands or walks nearby. At times the
    character's feet also sink slightly into the pavement. These
    collision/physics oddities are not part of normal gameplay and
    indicate a bug in the board-to-ground physics.",
  "glitch_detected": true,
  "description_of_glitch": "Skateboard becomes stuck half-inside
    the ground, jittering, spinning and sliding by itself;
    occasional foot clipping through the pavement."
}
```

o4-mini's output:

```
{
    "description_of_glitch": "After the player dismounts the
    skateboard, the board begins to move erratically on its own,
    spinning and flipping rapidly on the ground.",
    "glitch_detected": true,
    "reasoning": "The skateboard's movement is unnatural and not
    caused by player input or expected physics interactions. It
    appears to be a physics engine glitch where the board's
    collision or state becomes unstable."
}
```

GPT-4.1's output:

```
{
  "reasoning": "In the sequence of images, the skateboard is seen
    moving and spinning on its own, without any interaction from the
     player character. It even clips through the ground and other
    objects, which is not normal behavior for a skateboard in a
    skateboarding game. This indicates a physics or collision glitch
    .",
  "glitch_detected": true,
  "description_of_glitch": "The skateboard exhibits erratic,
    unintended movement and clips through the ground and other
    objects, behaving independently of the player character. This is
     likely due to a physics or collision detection glitch."
}
```

Figure A30: Sample from a video-based glitch detection task in which various models correctly identified a glitch related to a skateboard.

G.10 Additional Results for the Needle In A Haystack Task

Table A12: Model performance on the needle in a haystack task, reporting accuracy based on the distance between the model-reported frame and the ground truth frame, evaluated at different thresholds (1 seconds to 5 seconds).

Model Name	#	Acc @ ≤1s	Acc @ ≤2s	Acc @ ≤5s	Glitches Detected	Glitches Not Detected
GPT-4.1	100	6	11	19	72	28
GPT-4.1-mini	100	5	6	10	28	72
GPT-4.1-nano	100	0	1	4	78	22
GPT-4o	100	1	1	1	7	93
o3	100	1	2	13	58	42
Gemini-2.0-Flash	100	28	31	35	56	44
Gemini-2.5-Flash	100	32	32	35	42	58
Gemini-2.5-Pro	100	31	32	34	34	66
Sonnet-3.5	100	8	15	27	39	61
Sonnet-3.7	100	18	24	31	39	61

Table A13: Model performance (accuracy @ different thresholds) on the needle in a haystack task, evaluated on the subset where the model detected the glitch. Accuracy indicates whether the model can correctly locate the glitch frame within a 50-frame window.

Model Name	#	Acc @ ≤1s	Acc @ ≤2s	Acc @ ≤5s
GPT-4.1	72	8.3	15.3	26.4
GPT-4.1-mini	28	17.9	21.4	28.6
GPT-4.1-nano	78	0.0	1.3	5.1
GPT-4o	7	14.3	14.3	14.3
o3	58	1.7	3.4	20.7
Gemini-2.5-Pro	34	91.2	91.2	91.2
Gemini-2.5-Flash	42	76.2	76.2	78.6
Gemini-2.0-Flash	56	50.0	53.6	55.4
Sonnet-3.7	39	46.2	59.0	74.4
Sonnet-3.5	39	20.5	38.5	61.5

G.11 Additional Results for the Parametric Clipping Detection Task

In this section, we provide heatmap visualizations for parametric robustness tasks, where we vary the proximity of an object to a target human character to evaluate whether the models can robustly detect when a clipping glitch occurs. In the heatmaps, the red data points indicate wrong results and green data points indicate correct results from the VLM.

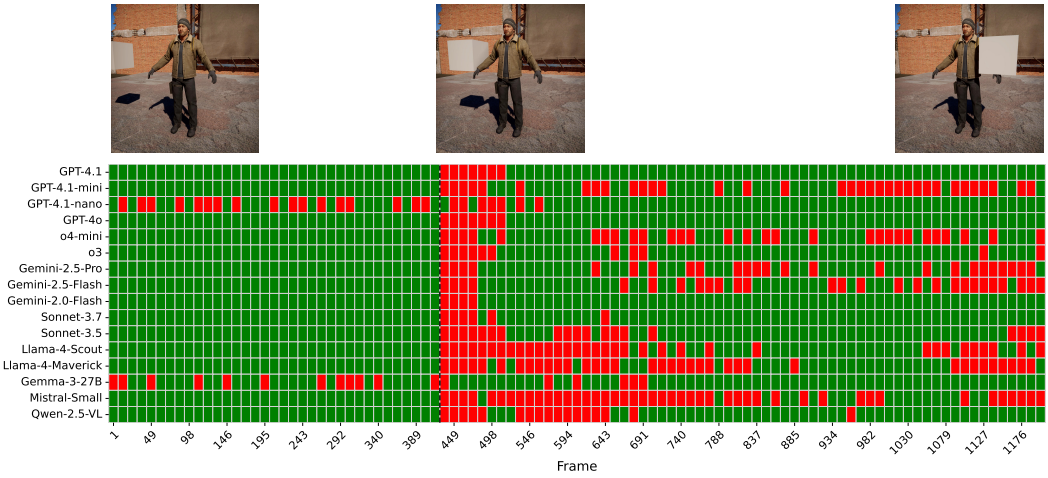


Figure A31: Heatmap for testing clipping between a white 3D cube and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

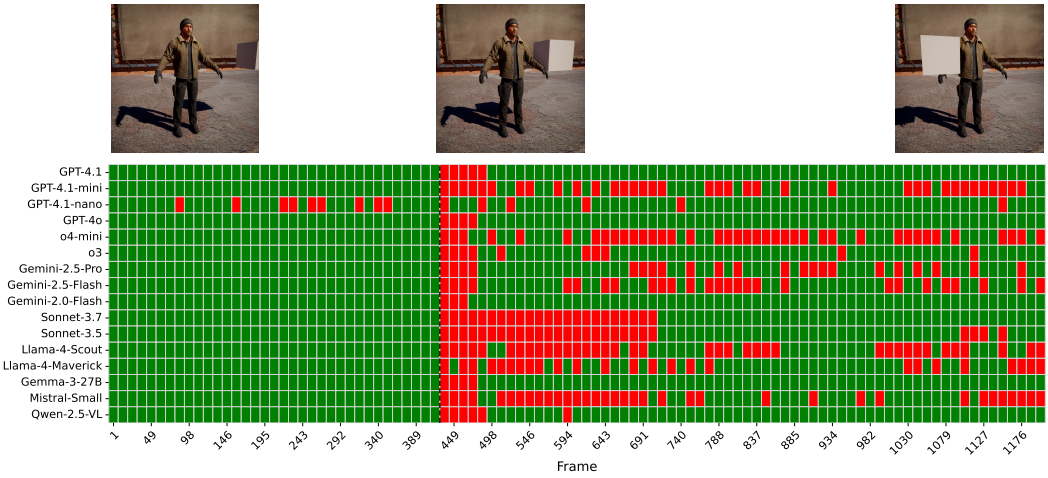


Figure A32: Heatmap for testing clipping between a white 3D cube and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

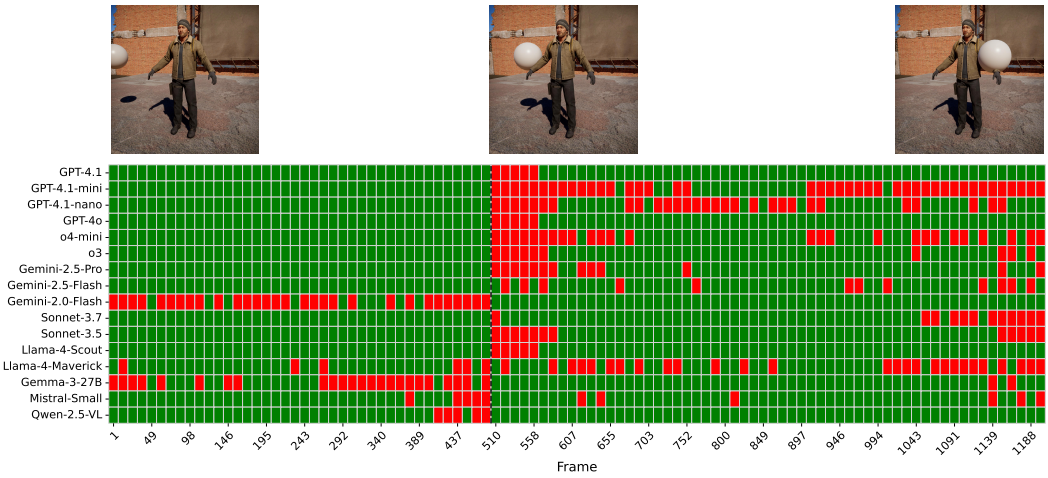


Figure A33: Heatmap for testing clipping between a white 3D sphere and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

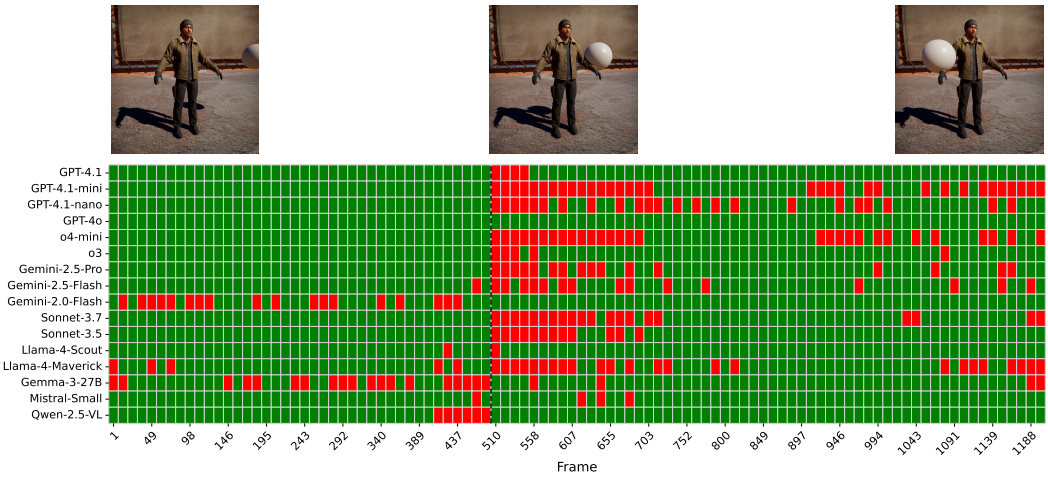


Figure A34: Heatmap for testing clipping between a white 3D sphere and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

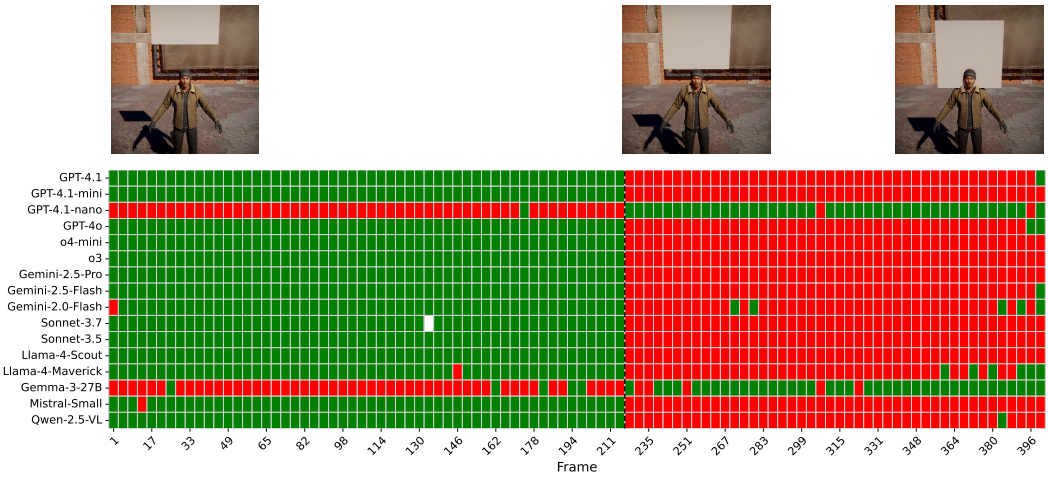


Figure A35: Heatmap for testing clipping between a white 2D plane (quad) and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

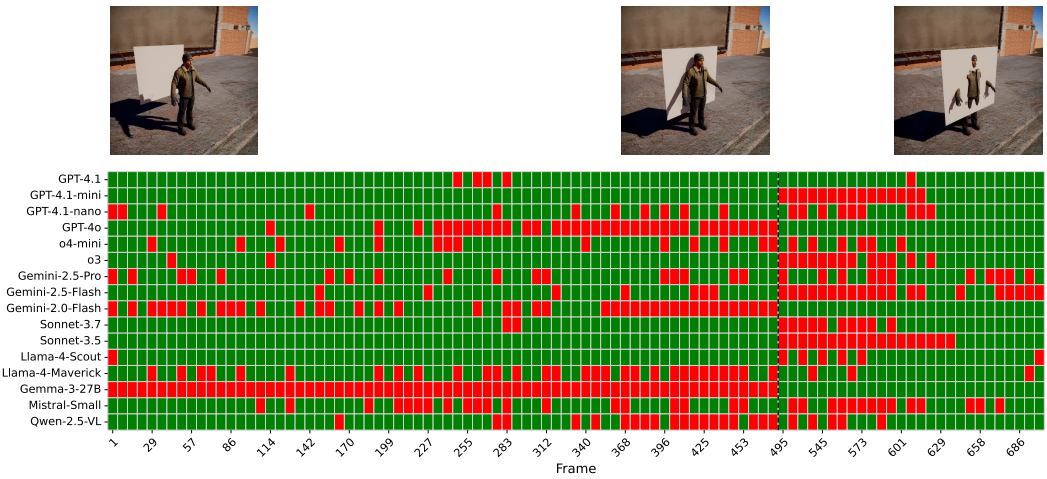


Figure A36: Heatmap for testing clipping between a white 2D plane (quad) and a human character. The dashed line on the heatmap indicates the frame where clipping occurs.

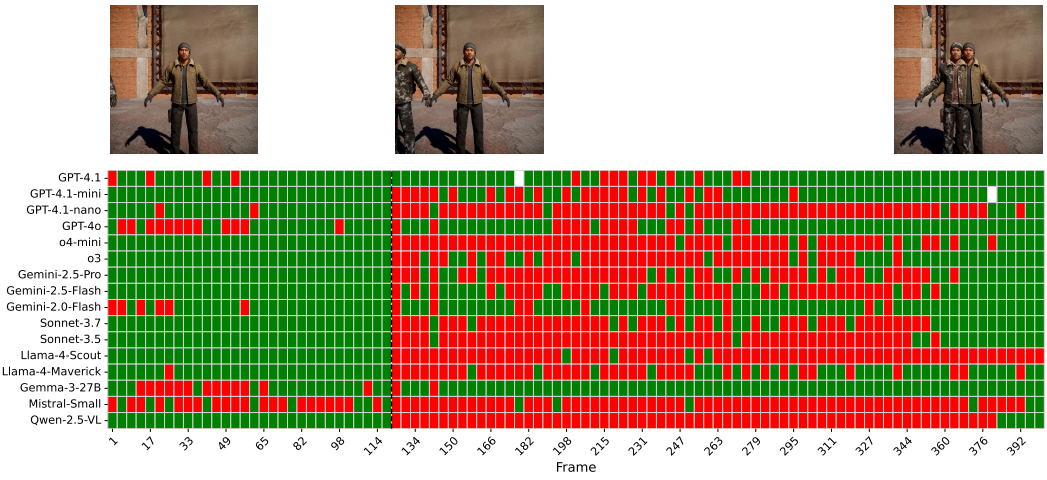


Figure A37: Heatmap for testing clipping between two human characters. The dashed line on the heatmap indicates the frame where clipping occurs.

G.12 Additional Results for the Visual Regression Task

Sonnet-3.7's output:

```
{
    "reasoning":"While both images show the same urban scene with
    similar lighting (sunset/dusk), environment, and dialogue
    subtitle, there are significant character differences that
    exceed acceptable customization. The first image shows a
    character in a white t-shirt and light pants, while the second
    image shows a completely different character wearing a red
    basketball jersey with the number 7, blue sleeves, and a cap.
    This appears to be an entirely different character model rather
    than just customization. The scene composition and background
    environment remain consistent, but the character change is
    substantial enough to be considered a major difference.",
    "test_pass":false
}
```

GPT-4o's output:

```
{
    "reasoning":"The second image shows a significant change in
    character positions and actions, indicating a major scene
    composition change. The character on the left is now in a
    different pose, suggesting a different action or event is
    occurring. These differences go beyond acceptable minor position
     adjustments or character customization.",
    "test_pass":false
}
```

o4-mini's output:

```
{
    "reasoning":"The background and lighting remain the same, but
    the primary character in the shot has been completely replaced
    by two different characters, which constitutes a major scene
    composition change rather than a simple customization or
    animation tweak.",
    "test_pass":false
}
```

Figure A38: Sample successful test run by various models that successfully detected unacceptable changes between two images.

o4-mini's output:

```
{
    "reasoning":"Both images show the same wooden interior scene
    with identical geometry, lighting, and asset placement. There
    are only negligible framing and exposure differences, no missing
     textures, no UI corruption or structural changes. This is an
    acceptable variation.",
    "test_pass":true
}
```

GPT-4.1's output:

```
{
    "reasoning":"The two images depict the same game scene from an
    identical perspective. The only noticeable difference is a very
    slight change in the lighting and shadow patterns, likely due to
     minor adjustments in the environmental lighting or rendering
    pass. There are no missing textures, interface issues,
    misaligned elements, or significant changes to scene geometry or
     key objects. All critical scene elements are present and
    correctly rendered.",
    "test_pass":true
}
```

Gemini-2.5-Pro's output:

```
{
    "reasoning":"TThe two provided screenshots are identical. There
     are no discernible differences in geometry, lighting, textures,
     object placement, or any other visual elements between the
    reference and the second image.",
    "test_pass":true
}
```

Figure A39: Sample visual regression test that top-performing models like GPT-4o, GPT-4.1, o4-mini, and Gemini-2.5-Pro fail to answer correctly. The models pass the test when they should fail due to one of the wooden pillars of the roof being missing in the alternative image.

o4-mini's output:

```
{
    "reasoning":"The only differences are environmental: the right-
    side doorway is open to show the night sky and the railing
    beyond, and a few cans are scattered further out on the floor.
    No UI errors, missing textures, or structural issues. These are
    minor background and lighting/scene-state variations, which are
    acceptable.",
    "test_pass":true
}
```

GPT-4.1's output:

```
{
    "reasoning":"The primary difference between the two images is
    the environmental condition visible through the window on the
    right side. In the first image, the window shows an interior
    wall, while in the second image, the window reveals an outdoor
    night scene with mountains and sky. The rest of the scene,
    including the vending machine, signage, and interior elements,
    remains unchanged. This change is attributable to a possible
    door or window being opened, which is a plausible gameplay or
    environmental variation. There are no signs of interface
    corruption, rendering errors, or missing key elements. The
    variation is acceptable as it falls under environmental
    condition changes.",
    "test_pass":true
}
```

Gemini-2.5-Pro's output:

```
{
    "reasoning":"The primary difference between the two images is
    the background visible through the window on the right. In the
    second image, a daytime sky and landscape are visible, whereas
    the first image shows a dark exterior. This change is consistent
     with acceptable environmental variations, such as a day/night
    cycle. Other minor differences in debris placement are
    negligible.",
    "test_pass":true
}
```

Figure A40: Sample visual regression test that top-performing models like GPT-4o, GPT-4.1, o4-mini, and Gemini-2.5-Pro fail to answer correctly. The models pass the test when they should fail due to incorrect wall rendering on the right side of the image.

o4-mini's output:

```
{
    "reasoning":"The two images depict the same game scene with
    only a very minor difference: in the first image, there is a red
     cup on the ground near the bottom center, which is missing in
    the second image. This is a minor variation in a non-critical
    background element (debris/trash), which is acceptable according
     to the criteria. There are no signs of interface corruption,
    text changes, rendering errors, or missing key scene elements.",
    "test_pass":true
}
```

GPT-4.1's output:

```
{
    "reasoning":"The two shots are visually identical in
    composition and geometry, with only very slight lighting/shadow
    differences. No UI corruption, missing textures, text changes or
     structural alterations are present. This falls under acceptable
     lighting variation",
    "test_pass":true
}
```

Gemini-2.5-Pro's output:

```
{
    "reasoning":"The two images provided are identical. There are
    no visual differences, rendering errors, or content changes
    between the reference and the second image. Therefore, the
    second image is an acceptable variation.",
    "test_pass":true
}
```

Figure A41: Sample visual regression test that top-performing models like GPT-4o, GPT-4.1, o4-mini, and Gemini-2.5-Pro fail to answer correctly. The models pass the test when they should fail due to missing the table in the center of the image.

o4-mini's output:

```
{
    "reasoning":"Both images depict the same scene with two
    characters near a poolside, with consistent background elements
    such as the hedge, tiled ground, and umbrella. The differences
    observed are acceptable: the characters have different clothing
    and are in slightly different positions, which can be attributed
     to character customization and minor animation or timing
    differences. The lighting is also different, which is an
    acceptable change in time of day or weather. There are no
    missing or corrupt UI elements, no graphical glitches, and the
    environment structure remains unchanged.",
    "test_pass":true
}
```

GPT-4.1's output:

```
{
    "reasoning": "The second frame introduces an unexpected UI
    overlay (the green FPS counter) and a significant composition
    change (a standing character's legs obstructing the view)
    compared to the first image. These constitute unacceptable
    differences.",
    "test_pass":false
}
```

Gemini-2.5-Pro's output:

```
{
    "reasoning":"The core scene composition, background environment
    , and character presence remain consistent. The primary
    difference is the clothing worn by the character on the left,
    which falls under the acceptable category of character
    customization. Minor variations in character position and
    lighting are also within acceptable limits.",
    "test_pass":true
}
```

Figure A42: Sample visual regression test that top-performing models like GPT-4o, GPT-4.1, and Gemini-2.5-Pro fail, but o4-mini answers correctly.

G.13 Additional Results for the Bug Report Generation Task

GPT-4o's output:

```
{
    "reasoning": "The weapon model appears to be missing a part of
    its barrel, which is not consistent with the expected design of
    the MP 3008. This could be due to a rendering issue or a missing
     texture.",
    "bug_report_title": "MP 3008 Weapon Model Incomplete",
    "bug_report_description": "The MP 3008 weapon model displayed
    in the inventory screen is missing a section of its barrel. This
     visual glitch may confuse players about the weapon's appearance
     and could affect immersion.  ",
    "affected_item": "Weapon Model"
}
```

Judge's (o3) output:

```
{
    "reasoning": "Ground truth bug is about two weapons visually
    clipping into each other (overlap). Generated report concerns a
    single weapon model (MP 3008) missing part of its barrel, no
    mention of clipping with another weapon. The core issues differ
    .",
    "match": false
}
```

Figure A43: A sample model response for the image-based bug report generation task, along with the judge's evaluation. The model provides an inaccurate description of the glitch, and the judge correctly rejects it.

GPT-4o's output:

```
{
    "reasoning": "The image shows a vehicle with a character inside
    , but the character appears to be clipping through the vehicle's
     windshield. This suggests a rendering issue where the character
     model is not properly constrained within the vehicle model.",
    "bug_report_title": "Character Clipping Through Vehicle
    Windshield",
    "bug_report_description": "A character inside a vehicle is
    visibly clipping through the windshield. This graphical glitch
    disrupts the visual realism and may affect gameplay by causing
    confusion about the character's position and interactions with
    the environment.  ",
    "affected_item": "Character and Vehicle"
}
```

Judge's (o3) output:

```
{
    "reasoning": "Ground truth issue concerns the car model
    intersecting with the ground, i.e., the vehicle itself is
    partially submerged/clipping into terrain. The generated report
    instead describes a character model intersecting with the
    vehicle's windshield. The objects involved (car vs. character)
    and the intersection context (ground vs. windshield) do not
    align, so they are different bugs.",
    "match": false
}
```

Figure A44: A sample model response for the image-based bug report generation task, along with the judge's evaluation. The model provides an inaccurate description of the glitch, and the judge correctly rejects it.

Gemini-2.5-Pro's output:


```
{
    "reasoning": "The character model's left shoulder and arm are
    intersecting with the wooden wall geometry behind them. This
    indicates a clipping issue where the character model is
    positioned incorrectly relative to the environment's collision
    boundaries.",
    "bug_report_title": "Character Model Clipping Through Wall",
    "bug_report_description": "The NPC standing behind the
    workbench has their left shoulder and arm partially embedded
    within the wooden wall texture behind them. This is a visual
    clipping error.",
    "affected_item": "Character Model (NPC)"
}
```


Judge's (o3) output:


```
{
    "reasoning": "Ground truth: character is clipping into the wall
    . Generated report: NPC character model's shoulder and arm are
    embedded in wall (visual clipping error). Both describe same
    issue: character clipping with wall geometry. Details (NPC,
    workbench) do not contradict core issue.",
    "match": true
}
```


Figure A45: A sample model response for the image-based bug report generation task, along with the judge's evaluation. The model provides a description that matches our ground truth, and the judge correctly accepts it.

Gemini-2.5-Pro's output:

```
{
    "reasoning": "The character on the right, riding a horse, is
    displayed in a static 'A-pose' or 'T-pose' with arms
    outstretched horizontally. This is not a natural pose for riding
     a horse and indicates an animation or character model rigging
    glitch.  ",
    "bug_report_title": "Character Stuck in A-Pose/T-Pose While
    Riding Horse",
    "bug_report_description": "A character model (potentially an
    NPC or another player) is observed riding a horse but is stuck
    in a default A-pose or T-pose animation state. Their arms are
    extended straight out to the sides instead of holding reins or
    resting naturally. This is a visual bug affecting character
    animation.",
    "affected_item": "Character Model/Animation "
}
```

Judge's (o3) output:

```
{
    "reasoning": "Both descriptions talk about a rider-character
    who is on a horse but is frozen in the default T-/A-pose instead
     of playing the correct riding animation. The ground truth
    additionally notes that the lower half of the character's body
    is clipping/merging into the horse, but this is a consequence of
     the same faulty pose state; the generated report simply omits
    that extra detail. The central bug---character stuck in T-pose
    while mounted---is the same in both descriptions.",
    "match": true
}
```

Figure A46: A sample model response for the image-based bug report generation task, along with the judge's evaluation. The model provides a description that matches our ground truth, and the judge correctly accepts it.

G.14 Observation About the Judge in the Bug Report Generation Task

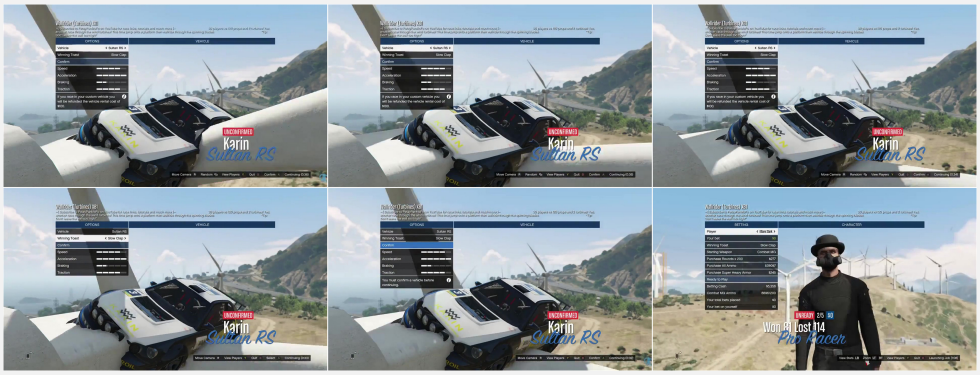
Gemini-2.5-Pro's output:

```
{
    "reasoning": "The character standing behind the player
    character 'Haz-man' is rendered as a solid black silhouette,
    lacking textures and appropriate lighting for the environment.
    This suggests a graphical glitch related to texture loading or
    shader application.",
    "bug_report_title": "Character Model Renders as Solid Black
    Silhouette",
    "bug_report_description": "A character model positioned behind
    the player character 'Haz-man' is displayed as a completely
    black, untextured silhouette. The lighting present in the room
    does not affect this character model, unlike the player
    character and the surrounding environment which are correctly
    lit and textured. This appears to be a rendering bug. ",
    "affected_item": "Character Model"
}
```

Judge's (o3) output:

```
{
    "reasoning": "Ground truth bug concerns the rendered SHADOW of
    a character: part of the shadow (specifically the face area) is
    transparent, letting the background show through. Expected
    shadow should be opaque. Generated report concerns an entirely
    different symptom: a whole character model itself appears as a
    solid black, unlit silhouette (overly opaque), not about
    transparency in a shadow. It addresses lighting on the model,
    not shadow transparency. Therefore the two reports describe
    different issues.",
    "match": false
}
```

Figure A47: Sample model response for the image-based bug report generation task along with the judge's evaluation. While certain glitches are challenging to describe precisely, the model correctly identifies and highlights the relevant aspects and regions in the image. However, the judge strictly evaluates the wording, entirely rejecting the response despite the model correctly pinpointing the problematic regions.



Gemini-2.5-Pro's output:

```
{
    "reasoning": "The video shows the pre-race vehicle selection
    screen. The player's chosen vehicle, a Karin Sultan RS, is
    displayed precariously balanced on top of a large wind turbine
    blade. This is an highly unusual and physically improbable
    location for a vehicle preview, suggesting a glitch in how the
    game stages the vehicle for this specific race menu.",
    "bug_report_title": "Vehicle Preview Incorrectly Positioned on
    Wind Turbine Blade in Pre-Race Menu",
    "bug_report_description": "In the pre-race setup menu for the '
    Wallrider (Turbines) XB1' race, the vehicle selected by the
    player is shown positioned on top of a wind turbine blade in the
     background environment instead of a standard display area. This
     appears to be a staging error for the vehicle preview,
    potentially specific to this custom race or location.",
    "affected_item": "Vehicle Preview / UI Staging"
}
```

Judge's (o3) output:

```
{
    "reasoning": "Ground truth describes an in-game physics/
    clipping issue: during gameplay the car becomes physically stuck
     inside a wind-turbine blade, with its body intersecting the
    geometry. Generated report describes a UI/preview staging issue
    that occurs in the pre-race menu: the vehicle model is merely
    rendered on top of a wind turbine blade background instead of
    the normal display area. It is about an incorrect camera/
    placement in the menu, not about gameplay collision or clipping.
     Because they concern different contexts (menu preview vs.
    gameplay), different symptoms (visual staging vs. physical
    clipping), and likely different root causes, they do not refer
    to the same underlying bug.",
    "match": false
}
```

Figure A48: Sample model response for the image-based bug report generation task along with the judge's evaluation. While the model's generated report is accurate, the judge incorrectly rejects it for being too strict about small details and wording that are correct but missing from the ground truth.

H VideoGameQA-Bench Samples

H.1 Visual Unit Tests

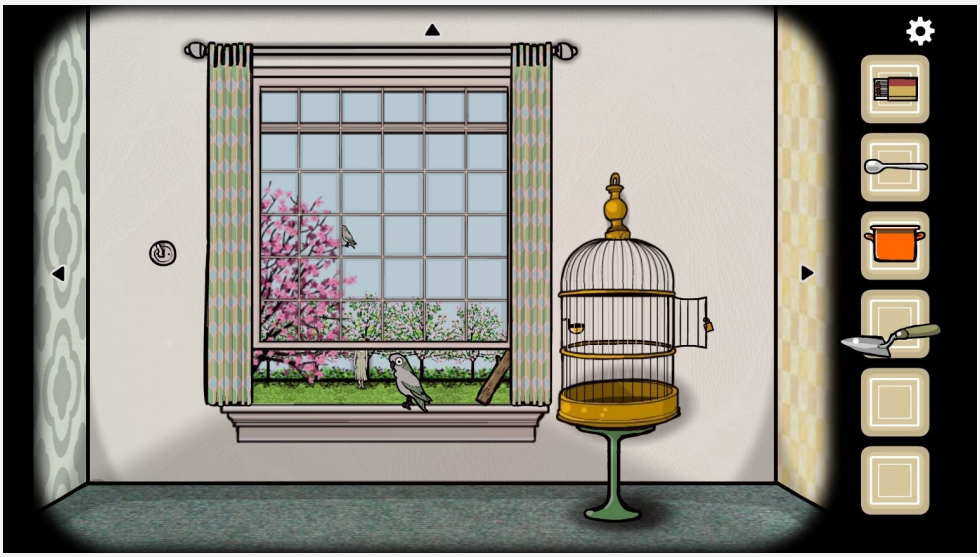
Based on the image, answer the following questions:

1. What is the character's posture?
2. Is the character facing towards or away from the camera?
3. Is there debris (like leaves) visible on the walkway?
4. What object is immediately in front of the character, bordering the edge?
5. Is there a large metal gate visible on the left side of the scene?
6. What time of day is depicted?
7. Is a cityscape with lit buildings visible in the background?
8. What is the condition of the metal gate on the left?

Provide your answer in the following JSON format:

```
{
  "character_posture": "", // options: ["standing", "walking", "
    sitting", "crouching"],
  "character_facing_direction": "", // options: ["towards", "away
    "],
  "debris_on_walkway": false, // options: [true, false],
  "object_in_front_of_character": "", // options: ["railing", "wall
    ", "open space", "door"],
  "gate_visible_left": false, // options: [true, false],
  "time_of_day": "", // options: ["day", "night", "dawn/dusk"],
  "lit_cityscape_visible": false, // options: [true, false],
  "left_gate_condition": "" // options: ["new", "rusty/weathered",
    "broken"]
}
```

Figure A49: Sample test from a visual unit test, where the model is asked to summarize some visual properties into a JSON structure.



Based on the image answer the following questions:

1. How many birds are visible inside the room (including inside the cage)?
2. How many birds are visible outside the window?
3. Is the birdcage door open?
4. What is the primary color of the bird inside the cage?
5. Is there a piece of wood leaning on the inside windowsill?
6. What is the main color of the blossoms seen outside the window?
7. Is the wallpaper on the left wall patterned?
8. Where is the grey bird positioned?

Provide your answer in the following JSON format

```
{
  "birds_inside_count": 0 // Integer count,
  "birds_outside_count": 0 // Integer count,
  "birdcage_door_open": false // true or false,
  "bird_in_cage_color": "" // options: ["yellow", "grey", "blue", "
    brown"],
  "wood_on_sill_present": false // true or false,
  "blossom_color": "" // options: ["pink", "white", "yellow", "red
    "],
  "left_wallpaper_patterned": false // true or false,
  "grey_bird_location": "" // options: ["inside cage", "on
    windowsill", "outside window", "on floor"]
}
```

Figure A50: Sample test from a visual unit test, where the model is asked to summarize some visual properties into a JSON structure.

Based on the image answer the following questions:

1. What is the primary color of the rally car?
2. Is the driver-side door of the car open or closed?
3. What number is displayed in large font on the car's door?
4. What brand name is visible on the yellow decal above the 'elf' logo on the car's side?
5. Is there a coiled orange air hose hanging from the ceiling on the left side?
6. What type of pattern is on the floor directly beneath the car?
7. Is there a screen or monitor mounted on the wall displaying graphs?

Provide your answer in the following JSON format

```
{
  "car_primary_color": "" // options: ["light blue", "dark blue", "
    white", "red", "black"],
  "driver_door_state": "" // options: ["open", "closed"],
  "car_door_number": 0 // Integer value,
  "yellow_decal_brand": "" // String value representing the text,
  "coiled_hose_visible": false // true or false,
  "floor_pattern": "" // options: ["plain", "checkered", "tiled", "
    textured_metal"],
  "wall_monitor_visible": false // true or false
}
```

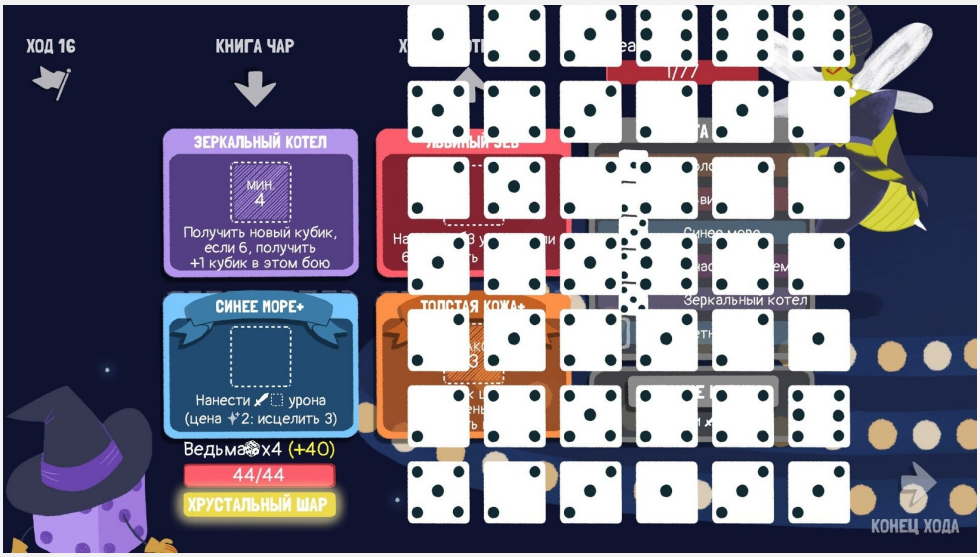
Figure A51: Sample test from a visual unit test, where the model is asked to summarize some visual properties into a JSON structure.

H.2 UI Unit Tests

Read the dashboard and fill the JSON values below:

```
{
    "tire_pressure": {
        "front_left": 0,
        "front_right": 0,
        "rear_left": 0,
        "rear_right": 0
    },
    "brake_temps": {
        "front_left": 0,
        "front_right": 0,
        "rear_left": 0,
        "rear_right": 0
    },
    "break_bias": 0,
    "break_sl": 0,
    "settings": {
        "map": 0,
        "mix": 0,
        "tc1": 0,
        "tc2": 0
    },
    "gear": 0,
    "rpm": 0,
    "speed_mph": 0
}
```

Figure A52: Sample UI unit test, where the model is asked to extract and summarize visual information from game UI elements into a JSON structure.



Please provide the values of the dice in the topmost row from left to right, and return them as a JSON list.

Figure A53: Sample UI unit test, where the model is asked to extract and summarize visual information from game UI elements into a JSON structure.

Based on the image, extract the list of weapons (single word) and return it in the following JSON format:

```
{  "items": ["weapon"] }
```

Figure A54: Sample UI unit test, where the model is asked to extract and summarize visual information from game UI elements into a JSON structure.

H.3 Visual Regression Tests


You are an image comparison tool for video game quality assurance. Given two screenshots from the same game scene, evaluate whether the second image represents an acceptable variation of the first (reference) image.

Consider these variations ACCEPTABLE:
- Player character customization elements
- Environmental conditions (weather, day/night cycle)
- Slight positional or animation differences
- Lighting and shadow adjustments
- Minor variations in non-critical background elements

Consider these variations UNACCEPTABLE:
- Interface corruption or element misalignment
- Textual content changes (unless expected, e.g., dynamic text)
- Significant visual artifacts or rendering errors (e.g., missing textures, z-fighting)
- Major structural changes to scene geometry not attributable to gameplay state
- Missing or grossly incorrect key scene elements compared to the reference

Provide your assessment as JSON:

```
{
  "reasoning": "Concise explanation of detected differences and
    justification for your decision based on the criteria.",
  "test_pass": true/false
}
```

Where 'test_pass' is true if the differences are acceptable and false if unacceptable differences are detected.

Figure A55: Sample test from a visual regression task, where the model is asked to compare two versions of the same scene to verify whether the changes are acceptable or unacceptable.

You are an image comparison tool for video game quality assurance. Given two screenshots from the same game scene, evaluate whether the second image represents an acceptable variation of the first (reference) image.

Consider these variations ACCEPTABLE:
- Player character customization elements
- Environmental conditions (weather, day/night cycle)
- Slight positional or animation differences
- Lighting and shadow adjustments
- Minor variations in non-critical background elements

Consider these variations UNACCEPTABLE:
- Interface corruption or element misalignment
- Textual content changes (unless expected, e.g., dynamic text)
- Significant visual artifacts or rendering errors (e.g., missing textures, z-fighting)
- Major structural changes to scene geometry not attributable to gameplay state
- Missing or grossly incorrect key scene elements compared to the reference

Provide your assessment as JSON:

```
{
  "reasoning": "Concise explanation of detected differences and
    justification for your decision based on the criteria.",
  "test_pass": true/false
}
```

Where 'test_pass' is true if the differences are acceptable and false if unacceptable differences are detected.

Figure A56: Sample test from a visual regression task, where the model is asked to compare two versions of the same scene to verify whether the changes are acceptable or unacceptable.

You are an image comparison tool for video game quality assurance. Given two screenshots from the same game scene, evaluate whether the second image represents an acceptable variation of the first (reference) image.

Consider these variations ACCEPTABLE:
- Player character customization elements
- Environmental conditions (weather, day/night cycle)
- Slight positional or animation differences
- Lighting and shadow adjustments
- Minor variations in non-critical background elements

Consider these variations UNACCEPTABLE:
- Interface corruption or element misalignment
- Textual content changes (unless expected, e.g., dynamic text)
- Significant visual artifacts or rendering errors (e.g., missing textures, z-fighting)
- Major structural changes to scene geometry not attributable to gameplay state
- Missing or grossly incorrect key scene elements compared to the reference

Provide your assessment as JSON:

```
{
  "reasoning": "Concise explanation of detected differences and
    justification for your decision based on the criteria.",
  "test_pass": true/false
}
```

Where ‘test_pass’ is true if the differences are acceptable and false if unacceptable differences are detected.

Figure A57: Sample test from a visual regression task, where the model is asked to compare two versions of the same scene to verify whether the changes are acceptable or unacceptable.

H.4 Image-based Glitch Detection

You are a helpful assistant analyzing video game images and screenshots for glitches. You will be given a screenshot from a video game, and your job is to analyze the screenshot and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

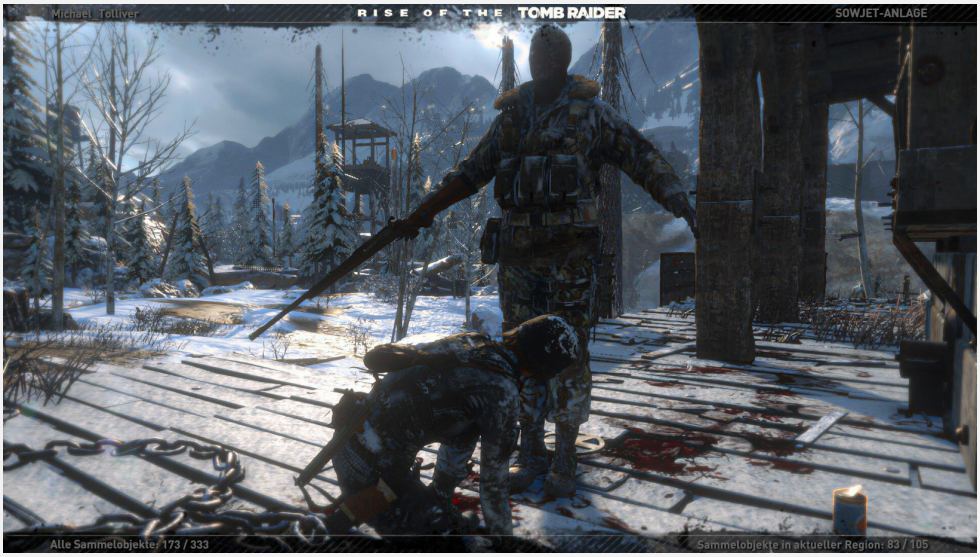
Figure A58: Sample for the image-based glitch detection task.

You are a helpful assistant analyzing video game images and screenshots for glitches. You will be given a screenshot from a video game, and your job is to analyze the screenshot and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A59: Sample for the image-based glitch detection task.



You are a helpful assistant analyzing video game images and screenshots for glitches. You will be given a screenshot from a video game, and your job is to analyze the screenshot and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A60: Sample for the image-based glitch detection task.

H.5 Parametric Clipping Detection Tests

You are a visual analysis assistant specializing in detecting object clipping in video game screenshots. Your task is to examine each provided image and determine whether any part of the white cube is intersecting with the character model, indicating a clipping issue.

Based on your analysis, respond using the following format:

```
{
    "reasoning": "Brief explanation of why you think clipping is
    present or not",
    "clipping_detected": true or false
}
```

Figure A61: Sample test from a parametric clipping detection task, where the model is asked to detect clipping glitches when an object is placed at various distances from a human character, to verify whether the model can robustly detect such glitches.

You are a visual analysis assistant specializing in detecting object clipping in video game screenshots. Your task is to examine each provided image and determine whether any part of the white cube is intersecting with the character model, indicating a clipping issue.

Based on your analysis, respond using the following format:

```
{
    "reasoning": "Brief explanation of why you think clipping is
    present or not",
    "clipping_detected": true or false
}
```

Figure A62: Sample test from a parametric clipping detection task, where the model is asked to detect clipping glitches when an object is placed at various distances from a human character, to verify whether the model can robustly detect such glitches.

H.6 Image-based Bug Report Generation

You are a video game quality assurance assistant who analyzes screenshots to identify and document visual glitches. When presented with an image, carefully examine it for any graphical bugs or rendering issues.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe and why it
    appears to be a glitch",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug, including its appearance and potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI) affected by the glitch"
}
```

Figure A63: Sample for the image-based bug report generation task.

You are a video game quality assurance assistant who analyzes screenshots to identify and document visual glitches. When presented with an image, carefully examine it for any graphical bugs or rendering issues.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe and why it
    appears to be a glitch",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug, including its appearance and potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI) affected by the glitch"
}
```

Figure A64: Sample for the image-based bug report generation task.

You are a video game quality assurance assistant who analyzes screenshots to identify and document visual glitches. When presented with an image, carefully examine it for any graphical bugs or rendering issues.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe and why it
    appears to be a glitch",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug, including its appearance and potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI) affected by the glitch"
}
```

Figure A65: Sample for the image-based bug report generation task.

H.7 Video-based Glitch Detection

You are a helpful assistant analyzing video game clips for glitches. You will be given a short video clip from a video game, and your task is to analyze the video and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A66: Sample for the video-based glitch detection task. In this video (only 6 sample frames are shown), a horse is moving up and down, which is a glitch.

You are a helpful assistant analyzing video game clips for glitches. You will be given a short video clip from a video game, and your task is to analyze the video and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A67: Sample for the video-based glitch detection task. In this video (only 6 frames are shown), the non-player character is performing an action, but the animation and table are misaligned.

You are a helpful assistant analyzing video game clips for glitches. You will be given a short video clip from a video game, and your task is to analyze the video and determine whether it contains a glitch.

Provide your answer in the following format:

```
{
    "reasoning": "Brief explanation of why you think a glitch is
    present",
    "glitch_detected": true or false,
    "description_of_glitch": "Description of the glitch if detected
     else empty string"
}
```

Figure A68: Sample for the video-based glitch detection task. In this video (only 6 frames are shown), the objects in the water are shaking violently, which is caused by a glitch in the physics engine simulation.

H.8 Needle In A Haystack

You are a specialized video game quality assurance analyst trained to detect visual anomalies in gameplay footage. Your task is to analyze the provided video clip to identify any bugs, glitches, visual artifacts, or unexpected behaviors.

What to Look For
Examine the video carefully for any:
- Visual artifacts (texture issues, flickering, clipping)
- Animation problems (jerky movements, T-poses)
- Rendering glitches (missing textures, lighting errors)
- Gameplay anomalies (collision failures, object teleportation)

Response Format
After your thorough analysis, provide your findings in this exact JSON format:

```
{
  "reasoning": "Brief explanation of what you observed in the video
     and why it appears to be a glitch",
  "glitch_detected": true|false,
  "timestamp": 0
}
```

Figure A69: Sample from the needle-in-a-haystack task. Please note that only 6 out of 50 frames are shown to highlight the glitch.

You are a specialized video game quality assurance analyst trained to detect visual anomalies in gameplay footage. Your task is to analyze the provided video clip to identify any bugs, glitches, visual artifacts, or unexpected behaviors.

What to Look For
Examine the video carefully for any:
- Visual artifacts (texture issues, flickering, clipping)
- Animation problems (jerky movements, T-poses)
- Rendering glitches (missing textures, lighting errors)
- Gameplay anomalies (collision failures, object teleportation)

Response Format
After your thorough analysis, provide your findings in this exact JSON format:

```
{
  "reasoning": "Brief explanation of what you observed in the video
     and why it appears to be a glitch",
  "glitch_detected": true|false,
  "timestamp": 0
}
```

Figure A70: Sample from the needle-in-a-haystack task. Please note that only 6 out of 50 frames are shown to highlight the glitch.

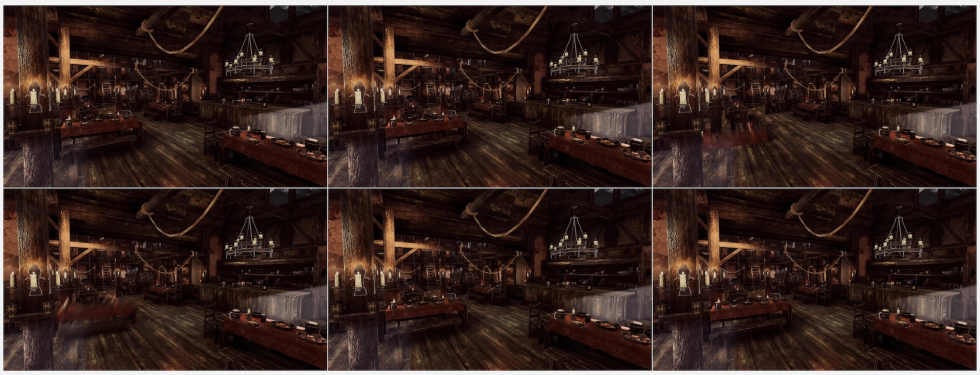
You are a specialized video game quality assurance analyst trained to detect visual anomalies in gameplay footage. Your task is to analyze the provided video clip to identify any bugs, glitches, visual artifacts, or unexpected behaviors.

What to Look For
Examine the video carefully for any:
- Visual artifacts (texture issues, flickering, clipping)
- Animation problems (jerky movements, T-poses)
- Rendering glitches (missing textures, lighting errors)
- Gameplay anomalies (collision failures, object teleportation)

Response Format
After your thorough analysis, provide your findings in this exact JSON format:

```
{
  "reasoning": "Brief explanation of what you observed in the video
     and why it appears to be a glitch",
  "glitch_detected": true|false,
  "timestamp": 0
}
```

Figure A71: Sample from the needle-in-a-haystack task. Please note that only 6 out of 50 frames are shown to highlight the glitch.



You are a specialized video game quality assurance analyst trained to detect visual anomalies in gameplay footage. Your task is to analyze the provided video clip to identify any bugs, glitches, visual artifacts, or unexpected behaviors.

What to Look For
Examine the video carefully for any:
- Visual artifacts (texture issues, flickering, clipping)
- Animation problems (jerky movements, T-poses)
- Rendering glitches (missing textures, lighting errors)
- Gameplay anomalies (collision failures, object teleportation)

Response Format
After your thorough analysis, provide your findings in this exact JSON format:

```
{
  "reasoning": "Brief explanation of what you observed in the video
     and why it appears to be a glitch",
  "glitch_detected": true|false,
  "timestamp": 0
}
```

Figure A72: Sample from the needle-in-a-haystack task. Please note that only 6 out of 50 frames are shown to highlight the glitch.

H.9 Video-based Bug Report Generation

You are a video game quality assurance assistant who analyzes video clips to identify and document visual glitches or strange behaviors. When presented with a video clip, carefully examine it for any graphical bugs, rendering issues, physics anomalies, or unexpected events.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe in the
    video and why it appears to be a glitch or bug",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug or behavioral anomaly, including its appearance and
    potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI, physics) affected by the glitch"
}
```

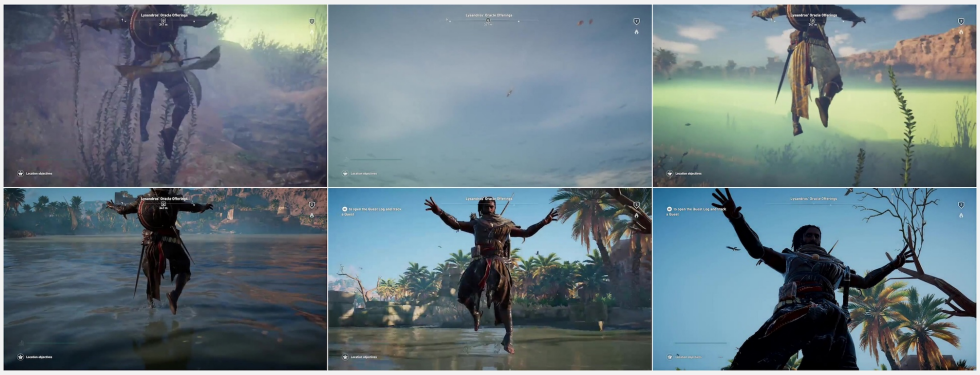
Figure A73: Sample for the video-based bug report generation task. In this video (only 6 frames are shown), a helicopter emerges from the ground.

You are a video game quality assurance assistant who analyzes video clips to identify and document visual glitches or strange behaviors. When presented with a video clip, carefully examine it for any graphical bugs, rendering issues, physics anomalies, or unexpected events.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe in the
    video and why it appears to be a glitch or bug",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug or behavioral anomaly, including its appearance and
    potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI, physics) affected by the glitch"
}
```

Figure A74: Sample for the video-based bug report generation task. In this video (only 6 frames are shown), a helicopter is stuck under the bridge.



You are a video game quality assurance assistant who analyzes video clips to identify and document visual glitches or strange behaviors. When presented with a video clip, carefully examine it for any graphical bugs, rendering issues, physics anomalies, or unexpected events.

Provide your analysis in the following JSON format:

```
{
    "reasoning": "Brief explanation of what you observe in the
    video and why it appears to be a glitch or bug",
    "bug_report_title": "A clear, concise title summarizing the
    issue",
    "bug_report_description": "Detailed description of the visual
    bug or behavioral anomaly, including its appearance and
    potential impact on gameplay",
    "affected_item": "The specific game element (character, object,
     environment, UI, physics) affected by the glitch"
}
```

Figure A75: Sample for the video-based bug report generation task. In this video (only 6 frames are shown), a player character is stuck in a falling position, descending from the water into the air.

I Dataset License

In this section, we provide details about the various data sources used to construct our dataset, along with their respective licenses.

Table A14: Data Sources and Their Licenses

Source	**License**
Steam Screenshots	Steam Subscriber Agreement
GamePhysics [45]	CC-BY-NC 4.0
YouTube Videos	YouTube Standard License

We created several images using the Unity game engine with assets purchased from the Unity Asset Store.