

# VRU-Accident: A Vision-Language Benchmark for Video Question Answering and Dense Captioning for Accident Scene Understanding

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<https://vru-accident.github.io/>

## Abstract

We present **VRU-Accident**, a large-scale vision-language benchmark designed to evaluate multimodal large language models (MLLMs) in high-risk traffic scenarios involving Vulnerable Road Users (VRUs) such as pedestrians and cyclists. VRU-Accident comprises **1K** real-world dashcam accident videos, annotated with **6K** multiple-choice question-answer pairs across six safety-critical categories (with **24K** candidate options and **3.4K** unique answer choices), as well as **1K** dense scene descriptions. Unlike prior works, our benchmark focuses explicitly on VRU-vehicle accidents, providing rich, fine-grained annotations that capture both spatial-temporal dynamics and causal semantics of accidents. To assess the current landscape of MLLMs, we conduct a comprehensive evaluation of **17** state-of-the-art models on the multiple-choice VQA task and on the dense captioning task. Our findings reveal that while MLLMs perform reasonably well on visually grounded attributes, they face significant challenges in reasoning and describing accident causes, types, and preventability.

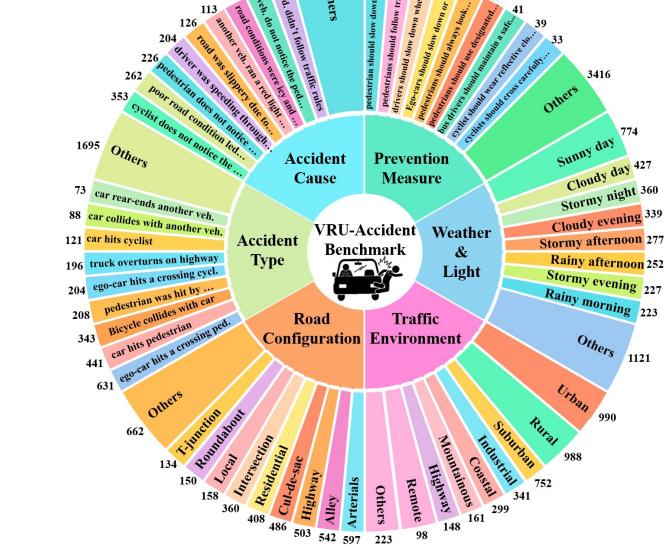


Figure 1. VQA distribution in the VRU-Accident benchmark.

## 1. Introduction

Multimodal Large Language Models (MLLMs) have become an important research area, showing strong performance in video understanding tasks such as video captioning, visual question answering, and visual grounding [2, 27, 52]. MLLMs have exhibited robust generalization across diverse downstream tasks, attributed to pretraining on large-scale, heterogeneous multimodal corpora [14, 23, 24]. This generalizability has sparked increasing interest in applying MLLMs to many scene understanding tasks which is critical to deepen our understanding of machine understanding and reasoning. To facilitate such applications, researchers have developed benchmarks and datasets focused on traffic event-related question-answering and general scene understanding [3, 29, 33]. However, these datasets overlook accident-centric reasoning, which is critical for safe driving

perception [1, 15].

Recently, several accident datasets [10–12, 53] provide short casual captions per video that describe accident types, causes, and possible prevention strategies, providing context for accident interpretation. Despite their utility, these video-based vision-language accident datasets rely on human annotators to classify accidents into predefined categories, which restricts their ability to evaluate the generalization capabilities of MLLMs on accident scenarios, unlike video question-answer (VQA) settings that require models to reason over dynamically constructed and semantically diverse answer spaces. Moreover, these datasets lack detailed accident scene descriptions, making it difficult to assess an MLLM’s ability to generate context-rich and semantically accurate narratives about accident events. Finally, these datasets are heavily biased toward vehicle-to-vehicle collisions, resulting in under-representation of in-

cidents involving VRUs, such as pedestrians and cyclists, where they VRUs accidents are more dangerous and lead to fatalities [4, 5, 18].

VRUs are among the most at-risk road users in traffic environments, where in 2020 alone, 6,516 pedestrians and 938 bicyclists lost their lives in traffic accidents with 3.9% and 9% increase from 2019, respectively, and over 54,000 were injured [4]. Alarmingly, pedestrian deaths accounted for 17% of all traffic fatalities, reflecting a 53% increase since 2009 [13]. Despite the severity and frequency of such incidents, we lack extensive vision-language benchmark specifically designed to evaluate the capabilities of MLLMs in answering questions or generating descriptions related to VRU-involved accidents with vehicles. This absence hinders the development and assessment of MLLMs in safety-critical applications such as autonomous vehicles, where evaluating a model’s ability to understand and reason about VRU-related accident scenarios is essential and ensure their driving perception for safe navigation even under adverse weather conditions.

To address this gap, we propose **VRU-Accident**, a large-scale benchmark designed to evaluate the reasoning and description capabilities of MLLMs in VRU traffic accidents. The benchmark includes 1,000 real-world accident and near-accident videos annotated with diverse VQA pairs and dense scene descriptions, covering various contextual and causal aspects of each incident. It serves as the first benchmark specifically curated to assess both VQA and captioning performance for safety-critical scenarios involving VRUs, where Figure 1 shows the distribution of the VQA task of each category in VRU-Accident benchmark. Our key contributions are summarized as follows:

- We introduce VRU-Accident, a large-scale benchmark comprising **1K** VRU-related accident videos, **6K** VQA questions with **24K** candidate options, and **1K** dense scene-level captions.
- We propose a semi-automatic benchmark curation pipeline that generates diverse and semantically rich VQA candidate sets. Each question includes one correct answer and three contextually plausible counterfactual, resulting in over **3.4K** unique answer options and making the task challenging for MLLMs.
- We conduct extensive evaluations of **17** MLLMs, with 15 open-source and 2 closed-source, on the VQA task and the dense captioning task, providing a unified benchmark for assessing their performance in safety-critical scene understanding task while offering key insights into their limitations.

## 2. Related Work

**Video QA Datasets and Benchmarks in Transportation Domain** Recent advances in vision-language models have spurred the development of various VQA datasets

Table 1. Comparison of accident video datasets. Surv.: Surveillance View, VQA: Video Question Answering, CC: Casual Captioning, DC: Dense Captioning, and R/S: Real/Synthetic videos.

Datasets	View	#Clips	#VRU accident	VQA	CC	DC	R/S
ROL [16]	Dashcam	1,000	-				R
DeepAccident [46]	Dashcam	-	-				S
CTA [53]	Dashcam	1,935	-	✓			R
CTAD [26]	Surv.	1,100	-				S
SUTD-TrafficQA [47]	Surv.	10,080	-	✓			R
TUMTraffic-VideoQA [55]	Surv.	1,000	<100	✓	✓	✓	R
TUMTraf-A [57]	Surv.	48	-				R
A3D [50]	Dashcam	3,757	<100				R
DoTA [50]	Dashcam	5,586	100				R
DADA-2000 [10]	Dashcam	2,000	223	✓			R
MM-AU [11, 12]	Dashcam	<b>11,727</b>	510	✓			R
<b>VRU-Accident (Ours)</b>	Dashcam	1,000	<b>1,000</b>	✓	✓	✓	R

and benchmarks within the traffic domain. Several recent works [29, 32, 33, 38] have proposed multi-modal VQA benchmarks in the context of autonomous driving, aiming to evaluate high-level reasoning about road scenes. Another research [17, 31, 48] investigates language grounding and explanation in complex traffic scenes. These datasets focus on providing textual rationales or identifying key objects and behaviors, thereby enhancing interpretability and supporting downstream decision making. The other works [28, 35] introduce task-specific benchmarks that target action recognition, risk localization, and importance-based reasoning. These efforts promote temporally grounded event understanding and knowledge extraction via joint captioning and QA. Despite their success in advancing scene understanding and reasoning in traffic environments, these benchmarks do not specifically address accident scenarios, particularly those involving vulnerable road users (VRUs) such as pedestrians and cyclists. As a result, they offer limited utility for evaluating a model’s capacity to reason about accident dynamics, causality, and preventability in safety-critical contexts where accurate accident comprehension is essential.

**Accident Understanding Datasets and Benchmarks** To support research on accident understanding in driving scenarios, several video datasets have been proposed in recent years. A summary of representative accident-centric datasets is presented in Table 1, while Table 2 provides detailed distributions for the subset of ego-view datasets that contain VRU involved accident videos. These datasets vary in terms of view type, volume, annotation modalities, and coverage of accident content. ROL [16], A3D [49], and DoTA [50] focus on anomaly detection in dashcam videos, while CTAD [26] and DeepAccident [46] leverage synthetic or simulation-based video generation to model urban traffic accidents. SUTD-TrafficQA [47] is a benchmark designed for VQA tasks in traffic events but relies on surveillance footage. In contrast, DADA-2000 [10] includes driver attention data to study accident prediction, and MM-AU [12], which among all their videos only 510 are accidents in-

Table 2. Comparison of VRU-related accident distributions across accident datasets, DoTA, DADA-2000, MM-AU, and our proposed VRU-Accident benchmark. VRU-Accident provides broader coverage across all attributes.

Datasets	VRU Types		Lightning			Weather Condition			Road Configuration					Traffic Environment					
	pedestrian	cyclist	day	night	sunny	rainy	snowy	cloudy	arterials	intersection	t-junction	curve	others	highway	urban	suburban	rural	mountain	tunnel
DoTA [50]	89	11	79	21	86	2	12	0	75	14	10	1	0	2	89	0	9	0	<b>0</b>
DADA-2000 [10]	114	109	197	26	213	10	0	0	84	87	43	7	2	1	186	0	33	2	<b>1</b>
MM-AU [11, 12]	320	190	452	58	418	29	46	17	248	163	71	16	12	3	430	<b>6</b>	68	2	1
<b>VRU-Accident(Ours)</b>	<b>730</b>	<b>270</b>	<b>873</b>	<b>127</b>	<b>808</b>	<b>61</b>	<b>108</b>	<b>23</b>	<b>584</b>	<b>241</b>	<b>133</b>	<b>24</b>	<b>18</b>	<b>6</b>	<b>873</b>	<b>6</b>	<b>111</b>	<b>3</b>	<b>1</b>

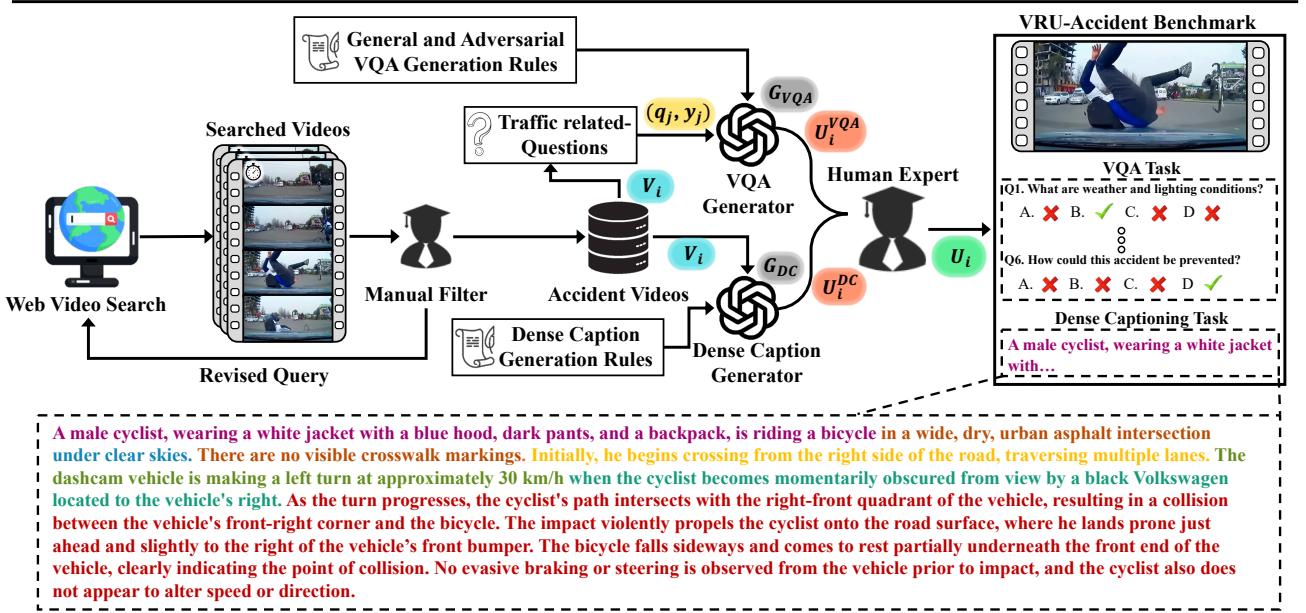


Figure 2. Overview of the VRU-Accident benchmark curation pipeline. Accident videos are retrieved from web sources based on traffic-related queries and manually filtered by human experts. For each video  $V_i$ , a set of ground truth answers  $y_j$  is first annotated by human experts for each question  $q_j$ . Then, the VQA generator  $G_{VQA}$  generates three counterfactual answers  $y_i^*$  based on  $(q_j, y_j)$ . Separately, a dense accident description  $C_i$  is generated for  $V_i$  using the dense captioning generator  $G_{DC}$ . All annotations are verified by human experts before being finalized. Colors: vehicle or pedestrian appearances, environmental factors, weather conditions, pedestrian's kinematic features, vehicle's kinematic features, spatial relationship between road users, and detailed collision descriptions.

volving VRUs, with 223 videos already imported from the DADA-2000 dataset, present large-scale collections of real-world dashcam incidents for visual reasoning and forecasting. Among them, a few works [10–12, 53] include short captions describing accident types, causes, or prevention strategies. However, these captions are entirely dependent on human annotators and constrained to predefined categories, which not only limits their expressiveness in capturing the diverse semantics of real-world accident scenarios but also restricts the ability to evaluate the generalization capabilities of modern MLLMs such as LLaVA family [20, 21, 54], InternVL family [7, 8, 56], Qwen family [40, 45], and the others [25, 30, 36, 37, 39]. On the other hand, SUTD-TrafficQA [47] addresses this gap by introducing a structured VQA benchmark for traffic scenarios, enabling more principled evaluation of VQA performance in MLLMs. However, its reliance on surveillance

camera footage limits its ability to capture direct interactions between vehicles and VRUs, such as pedestrians and cyclists, especially during moments of impact or collision. Our VRU-Accident benchmark is set to target VRU-related accidents in a vision-language framework. It combines the MM-AU and DoTA samples while adding more samples reaching 1,000 videos. It includes VQA annotations across six accident-related categories and detailed dense captions for 1,000 real-world ego-view accident videos. This enables a comprehensive and fine-grained evaluation of MLLMs' reasoning and description capabilities in realistic, high-risk interaction scenarios between vehicles and VRUs.

### 3. VRU-Accident Benchmark

In this section, we describe the overall design of the VRU-Accident benchmark, focusing on two key components: the benchmark curation process and statistics. Our goal is to

establish a standardized and comprehensive framework for analyzing accident scenes involving VRUs through both VQA and Dense Captioning tasks. We aim to capture a wide range of contextual, environmental, and causal elements from real-world traffic accident videos to facilitate multimodal reasoning in safety-critical scenarios. We focus on collecting real-world traffic accident videos involving VRUs and curating a benchmark tailored for two vision-language tasks: VQA and Dense Captioning. The overall curation pipeline is illustrated in Figure 2. We define each accident video as  $V_i$ , where  $i = 1, 2, \dots, N$ .

### 3.1. VQA Category Selection

We define six core VQA categories as  $j \in \{1. Weather \& Light, 2. Traffic Environment, 3. Road Configuration, 4. Accident Type, 5. Accident Cause, 6. Accident Prevention Measure\}$ . Among these, *Accident Type*, *Accident Cause*, and *Accident Prevention Measure* are essential for understanding the core dynamics and outcomes of VRU-involved accidents, and have been widely used in prior research on traffic incident analysis [10, 12, 47, 53]. In addition, we include contextual attributes such as *Weather & Light*, *Traffic Environment*, and *Road Configuration*, which are known to significantly influence accident circumstances and situational awareness [41–44].

### 3.2. VQA Curation Pipeline

Our task is framed as a multi-category VQA problem. For each video  $V_i$ , we define a set of questions and corresponding answers as  $Q_i$  and  $Y_i$ , respectively. Each  $Q_i$  and  $Y_i$  contain a question-answer pair  $(q_j, y_j)$  for each of the six VQA categories, where  $j = 1, \dots, 6$ . To enable discriminative evaluation, we additionally define a set of three counterfactual answers  $y_j^*$  per category, which belong to the same domain as  $y_j$  but are incorrect. These are generated using a VQA counterfactual generation function  $G_{VQA}$ , such that  $y_j^* = G_{VQA}(q_j, y_j)$ . We then define the final candidate answer set for each question as  $\hat{Y}_j = \{y_j, y_j^{*(1)}, y_j^{*(2)}, y_j^{*(3)}\}$ . Each video's VQA annotation is summarized as  $\mathcal{U}_i^{VQA} = \{V_i, Q_i, \hat{Y}_i\}$ , where  $\hat{Y}_i = \{\hat{Y}_j\}_{j=1}^6$  denotes the candidate answer sets for all six categories.

### 3.3. Dense Caption Curation Pipeline

The dense captioning task aims to generate a comprehensive and temporally grounded textual description of the traffic accident scenario depicted in each video  $V_i$ . Rather than enumerating every visual element, we focus on capturing the essential dynamics of the incident, such as weather and environmental factors, road users' appearance and posture, road users' kinematic features, and the sequential interactions between the vehicle and the VRU leading up to the accident. The descriptions are required to be concise yet information-dense, suitable for use as high-quality ground

Table 3. Summary of annotation statistics in the VRU-Accident benchmark.

Task	Categories	Options/GT	# Samples	# Unique Samples
VQA	Weather & Light	Options	4K	38
		Ground Truth	1K	13
	Traffic Environment	Options	4K	27
		Ground Truth	1K	6
	Road Configuration	Options	4K	42
		Ground Truth	1K	10
	Accident Type	Options	4K	405
		Ground Truth	1K	33
Accident Cause	Options	4K	782	
	Ground Truth	1K	135	
Prevention Measure	Options	4K	2143	
	Ground Truth	1K	211	
Dense Captioning	Detailed Description of accident Video	1K	1K	

truth data in accident analysis. To achieve this, we employ a Dense Captioning generator  $G_{DC}$  that produces a caption  $C_i$  for each video  $V_i$ , such that  $C_i = G_{DC}(V_i)$ . The final annotation for the dense captioning task is represented as  $\mathcal{U}_i^{DC} = \{V_i, C_i\}$ . Finally, the complete annotation for each video of VRU-Accident is defined as  $\mathcal{U}_i = \mathcal{U}_i^{VQA} \cup \mathcal{U}_i^{DC} = \{V_i, Q_i, \hat{Y}_i, C_i\}$ , and Figure 3 illustrates an example of both VQA and Dense Captioning annotations in our VRU-Accident benchmark.

### 3.4. Benchmark Statistics

The VRU-Accident benchmark contains a total of 1,000 real-world traffic accident videos of VRUs. Each video is annotated with both VQA and dense captioning labels. As shown in Table 3, the VQA task comprises 6,000 question-answer (QA) pairs and 1,000 dense captioning. For each QA pair, we construct a set of four candidate answers (one ground truth and three counterfactual options), resulting in a total of 24,000 multiple-choice options across the dataset. In addition to the volume of annotations, a key characteristic of VRU-Accident is the large number of unique answer samples per category. For example, the *Prevention Measure* and *Accident Cause* categories contain 2,143 and 782 unique textual answers, respectively. Unlikely accident classification tasks [10, 12, 50] which require predefined number of classes in each category, high variability of our benchmark requires models not only to classify from a fixed label space but to reason about fine-grained and context-dependent semantics, underscoring the importance of VLMs for this benchmark. The dense captioning task also contributes to the benchmark's complexity and richness, providing 1,000 detailed accident descriptions, resulting in 1,000 unique captions aligned with real-world accident scenarios. For more details about benchmark statistics, please refer to Supplementary Section B.

Suddenly start to cross the road	Didn't notice a coming vehicle	A vehicle hits a pedestrian	Falls to the ground after collision			
Weather and Light Condition	Traffic Environment	Road Configuration	Accident Type			
<b>Question:</b> What's weather and lighting? (A) Cloudy evening <span style="color:red">✗</span> <b>(B) Sunny day</b> <span style="color:green">✓</span> (C) Stormy afternoon <span style="color:red">✗</span> (D) Rainy morning <span style="color:red">✗</span>	<b>Question:</b> Where did the accident happened? (A) Rural <span style="color:red">✗</span> (B) Suburban <span style="color:red">✗</span> <b>(C) Urban</b> <span style="color:green">✓</span> (D) Industrial <span style="color:red">✗</span>	<b>Question:</b> What type of road is shown? <b>(A) Arterials</b> <span style="color:green">✓</span> (B) Residential <span style="color:red">✗</span> (C) Motorway <span style="color:red">✗</span> (D) Alley <span style="color:red">✗</span>	<b>Question:</b> What kind of accident occurred? (A) Bicycle collides with car <span style="color:red">✗</span> (B) Motorcycle hits a pedestrian <span style="color:red">✗</span> <b>(C) Car hits a pedestrian</b> <span style="color:green">✓</span> (D) Motorcycle rashes into wall <span style="color:red">✗</span>			
Accident Cause	Accident Prevention Measure					
<b>Question:</b> Why did the accident happened? (A) Driver was speeding recklessly <span style="color:red">✗</span> <b>(B) Pedestrian moves or stays on the road</b> <span style="color:green">✓</span> (C) Mechanical failure of the vehicle <span style="color:red">✗</span> (D) Road construction caused sudden stop <span style="color:red">✗</span>	<b>Question:</b> How could this accident be prevented? (A) Cyclists should wear reflective gear while riding at night. <span style="color:red">✗</span> (B) Bus drivers should maintain a safe distance from pedestrians. <span style="color:red">✗</span> (C) Motorists should always stop for red lights at intersections. <span style="color:red">✗</span> <b>(D) Pedestrians should follow traffic rules.</b> <span style="color:green">✓</span>					
Dense Captioning						
<b>A teenage male pedestrian, wearing a black Puma jacket and black pants with white stripes, is standing beside a dry, two-lane urban asphalt road under clear skies and bright sunlight when he suddenly steps onto the roadway. The road is bordered by parked vehicles and a pedestrian safety barrier on the left, and a fenced area with leafless trees and commercial buildings on the right. A dashcam-equipped vehicle is stationary in the lane, while a gray vehicle approaches from behind at an estimated speed of 40 km/h. Due to the dashcam vehicle obstructing the view, the approaching gray car's driver is unable to see the pedestrian entering the road and does not slow down. At the same time, the pedestrian also enters the road abruptly from the right sidewalk without apparent caution. By the time the driver sees the pedestrian, there is not enough distance to stop in time. Despite attempting to brake, the vehicle strikes the pedestrian near the front-right side. The impact causes the pedestrian to fall onto the asphalt, marking the end of the incident. The surrounding traffic and road conditions reflect a typical calm urban morning.</b>						
<span style="color:blue">█</span> Weather Conditions <span style="color:orange">█</span> Environmental Factors <span style="color:magenta">█</span> Vehicle or Pedestrian Appearances <span style="color:lightgreen">█</span> Vehicle's Kinematic Features <span style="color:cyan">█</span> Spatial Relationship b/w Road Users <span style="color:yellow">█</span> Pedestrian's Kinematic Features <span style="color:red">█</span> Detailed Collision Descriptions						

Figure 3. Visualization of annotations in VRU-Accident benchmark illustrating both the VQA and dense captioning tasks.

## 4. Experiments

### 4.1. Implementation Details

**Baseline MLLMs.** We evaluate a total of 17 SOTA MLLMs on the VRU-Accident benchmark. This includes 15 open-source models that are assessed on both the VQA and dense captioning tasks, and 2 closed-source models. All models are tested in a *zero-shot* setting without any fine-tuning, ensuring a fair comparison of their generalization abilities in unseen VRU-related accident scenarios. All evaluations were conducted on a workstation equipped with 8 NVIDIA TITAN RTX GPUs, each with 24 GB of memory.

**VQA Task.** We construct a total of **6K** VQA pairs based

on **1K** VRU-related accident videos, with each video annotated with six question-answer pairs corresponding to distinct reasoning categories. Each question is accompanied by four candidate options (A, B, C, D), and models are prompted to select the correct choice. The generated responses are processed with model-specific postprocessing strategies to extract the predicted option, and *category-wise accuracy* is computed to quantify performance.

**Dense Captioning Task.** We evaluate **1K** video-prompt pairs, where models are asked to generate a comprehensive description of each VRU-related accident video, including visual scene elements, road user behavior, vehicle dynamics, and accident events. Generated captions are evaluated using SPICE [6], METEOR [19], COMET [34], and

Table 4. Comparison of VQA performance of state-of-the-art models on VRU-Accident Benchmark. WL: Weather&Light, TE: Traffic Environment, RC: Road Configuration, AT: Accident Type, AC: Accident Cause, and PM: Prevention Measure. Rows with gray color background represent closed-source models, while rows with white background denote open-source models. **Black**, **blue**, and **red** colors indicate the best, second-best, and worst performance, respectively. **Underline** denotes the best performance among open-source models.

Model (Param.)	Year	Acc <sub>WL</sub>	Acc <sub>TE</sub>	Acc <sub>RC</sub>	Acc <sub>AT</sub>	Acc <sub>AC</sub>	Acc <sub>PM</sub>	Acc <sub>AVG.</sub>
LLaVA-OneVision(0.5B) [20]	2024	<b>72.1</b>	79.9	40.1	<b>35.9</b>	34.8	40.8	50.6
InternVL2.5(1B) [8]	2025	69.2	67.7	39.0	45.8	<b>21.3</b>	51.0	49.0
Mobile-VideoGPT(1.5B) [36]	2025	<b>78.4</b>	64.5	44.4	49.3	27.2	47.4	51.9
InternVL2.5(2B) [8]	2025	68.3	79.6	46.8	<b>70.7</b>	38.0	50.3	59.0
InternVL3(2B) [56]	2025	70.7	78.3	53.5	41.2	<b>50.4</b>	53.2	57.9
Qwen2.5-VL(3B) [40]	2025	63.8	72.1	39.4	47.3	25.6	44.7	<b>48.8</b>
Video-XL-Pro(3B) [25]	2025	69.0	<b>87.5</b>	35.4	43.9	47.5	48.9	55.4
InternVL2.5(4B) [8]	2025	69.9	82.7	42.9	56.7	50.1	51.0	58.9
Video-XL2(7B) [37]	2024	71.0	82.7	59.3	58.1	45.4	53.5	61.7
LLaVA-NeXT-Video(7B) [21]	2024	71.6	<b>84.1</b>	54.0	38.8	27.7	<b>33.1</b>	51.6
LLaVA-Video (7B) [54]	2024	68.2	80.7	64.7	63.7	<b>50.4</b>	58.6	<b>64.4</b>
Qwen2-VL(7B) [45]	2024	70.3	<b>59.6</b>	<b>34.1</b>	60.1	41.4	46.8	52.1
InternVL2(8B) [7]	2024	61.9	78.1	42.8	58.3	43.6	<b>62.0</b>	57.8
InternVL2.5(8B) [8]	2025	67.6	81.9	51.4	48.0	48.1	<b>61.9</b>	59.8
InternVL3(8B) [56]	2025	70.0	81.8	<b>67.8</b>	64.8	43.7	58.4	<b>64.4</b>
GPT-4o-mini [30]	2024	<b>60.2</b>	78.6	42.1	46.3	34.8	50.3	52.1
Gemini 1.5-flash [39]	2024	65.7	78.5	<b>71.4</b>	<b>77.9</b>	<b>54.6</b>	53.0	<b>66.9</b>
<b>Human Expert</b>	2025	<b>95.1</b>	<b>94.7</b>	<b>93.8</b>	<b>94.5</b>	<b>95.1</b>	<b>94.8</b>	<b>94.7</b>

ROUGE [22] to assess linguistic quality and event coverage. BLEU score is not included, as it yields values below 0.1, due to its emphasis on exact n-gram precision without incorporating recall or contextual semantics [9]. We also present detailed evaluation metrics, full prompt templates, and implementation details for both VQA and Dense Captioning tasks on VRU-Accident benchmark in Supplementary Section B.

## 4.2. Result Analysis

**VQA Task.** Table 4 presents the performance comparison of 17 state-of-the-art MLLMs, including 15 open-source and 2 closed-source models, on the VQA task of the VRU-Accident benchmark. Overall, Gemini [39] achieves the best average performance (66.9%), followed by LLaVA-Video [54] and InternVL3(8B) [56], which show strong performance across most categories. In contrast, smaller models such as Qwen2.5-VL(3B) [40] and InternVL2.5(1B) [8] struggle particularly on causal and preventive reasoning. We observe that MLLMs generally perform better on visually grounded attributes (e.g., Weather & Light or Traffic Environment), while achieving lower accuracy on high-level reasoning tasks such as Accident Cause and Prevention Measure. Additionally, models often struggle with categories like ‘Road Configuration’ and ‘Accident Type’, but for distinct reasons. In the case of ‘Road Configuration’, poor performance is largely due to the models’ limited ability to understand complex and dynamic properties

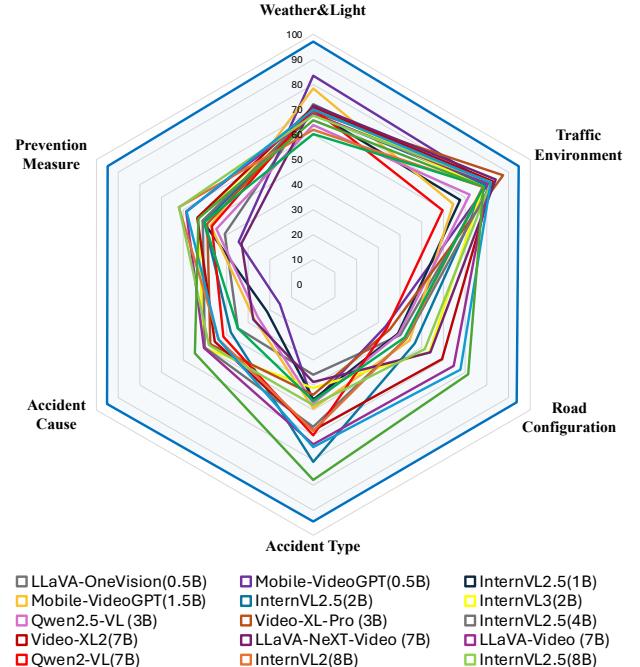


Figure 4. Summary of MLLMs performance on VRU-Accident for the VQA task along with the Human Expert scores.

of the surrounding environment, such as curves, intersections, or multi-lane structures. For ‘Accident Type’, the

Table 5. Quantitative comparisons on the dense caption task. We report ROUGE precision (P), recall (R), and F-measure (F), where P and R indicate the overlap of 4-grams with candidate and reference summaries, respectively, and F is their harmonic mean. Higher values indicate better performance. **Black**, **blue**, and **red** colors indicate the best, second-best, and worst performance, respectively. **Underline** denotes the best performance among open-source models.

Model (Param.)	SPICE $\uparrow$	METEOR $\uparrow$	COMET $\uparrow$	ROUGE-1 $\uparrow$			ROUGE-2 $\uparrow$			ROUGE-L $\uparrow$		
				P	R	F	P	R	F	P	R	F
LLaVA-OneVision(0.5B) [20]	0.126	0.224	0.647	0.388	0.384	0.380	0.092	0.091	0.090	0.228	0.229	0.225
InternVL2.5(1B) [8]	0.132	0.236	0.676	0.409	0.403	0.400	0.089	0.088	0.087	0.212	0.209	0.207
Mobile-VideoGPT(1.5B) [36]	0.128	0.25	0.665	<b>0.363</b>	0.420	0.386	<b>0.069</b>	0.080	0.073	<b>0.180</b>	0.209	<b>0.192</b>
InternVL2.5(2B) [8]	0.139	0.249	0.682	0.404	0.428	0.411	0.094	0.099	0.095	0.207	0.220	0.211
InternVL3(2B) [56]	<b>0.100</b>	<b>0.188</b>	<b>0.584</b>	0.429	<b>0.309</b>	<b>0.345</b>	0.098	<b>0.070</b>	<b>0.078</b>	0.249	<b>0.177</b>	0.199
Qwen2.5-VL(3B) [40]	0.149	0.261	0.682	0.396	0.446	0.416	0.106	0.120	0.111	0.207	0.234	0.218
Video-XL-Pro(3B) [25]	0.141	0.265	0.695	0.396	0.450	0.418	0.098	0.111	0.103	0.206	0.236	0.218
InternVL2.5(4B) [8]	0.146	0.260	0.696	0.408	0.449	0.423	0.098	0.108	0.102	0.207	0.228	0.215
Video-XL2(7B) [37]	0.148	0.233	0.693	<b>0.491</b>	0.378	0.421	0.121	0.092	0.103	<b>0.266</b>	0.203	0.227
LLaVA-NeXT-Video(7B) [21]	0.155	0.259	0.708	0.443	0.438	0.437	0.124	0.123	0.123	0.248	0.246	0.245
LLaVA-Video(7B) [54]	0.157	<b>0.270</b>	0.686	0.422	0.460	0.436	0.113	0.124	0.117	0.219	0.240	0.227
Qwen2-VL(7B) [45]	<b>0.170</b>	<b>0.285</b>	<b>0.721</b>	0.430	<b>0.494</b>	<b>0.456</b>	<b>0.126</b>	<b>0.145</b>	<b>0.134</b>	0.233	<b>0.270</b>	<b>0.248</b>
InternVL2(8B) [7]	0.139	0.249	0.694	0.398	0.431	0.410	0.091	0.098	0.093	0.201	0.220	0.208
InternVL2.5(8B) [8]	0.152	0.259	0.698	0.420	0.442	0.426	0.102	0.108	0.104	0.216	0.228	0.219
InternVL3(8B) [56]	0.159	0.267	0.694	0.434	0.454	0.437	0.113	0.118	0.114	0.225	0.234	0.225
Gemini 1.5-flash [39]	<b>0.194</b>	<b>0.285</b>	<b>0.741</b>	<b>0.492</b>	<b>0.479</b>	<b>0.481</b>	<b>0.152</b>	<b>0.147</b>	<b>0.148</b>	<b>0.272</b>	<b>0.266</b>	<b>0.266</b>

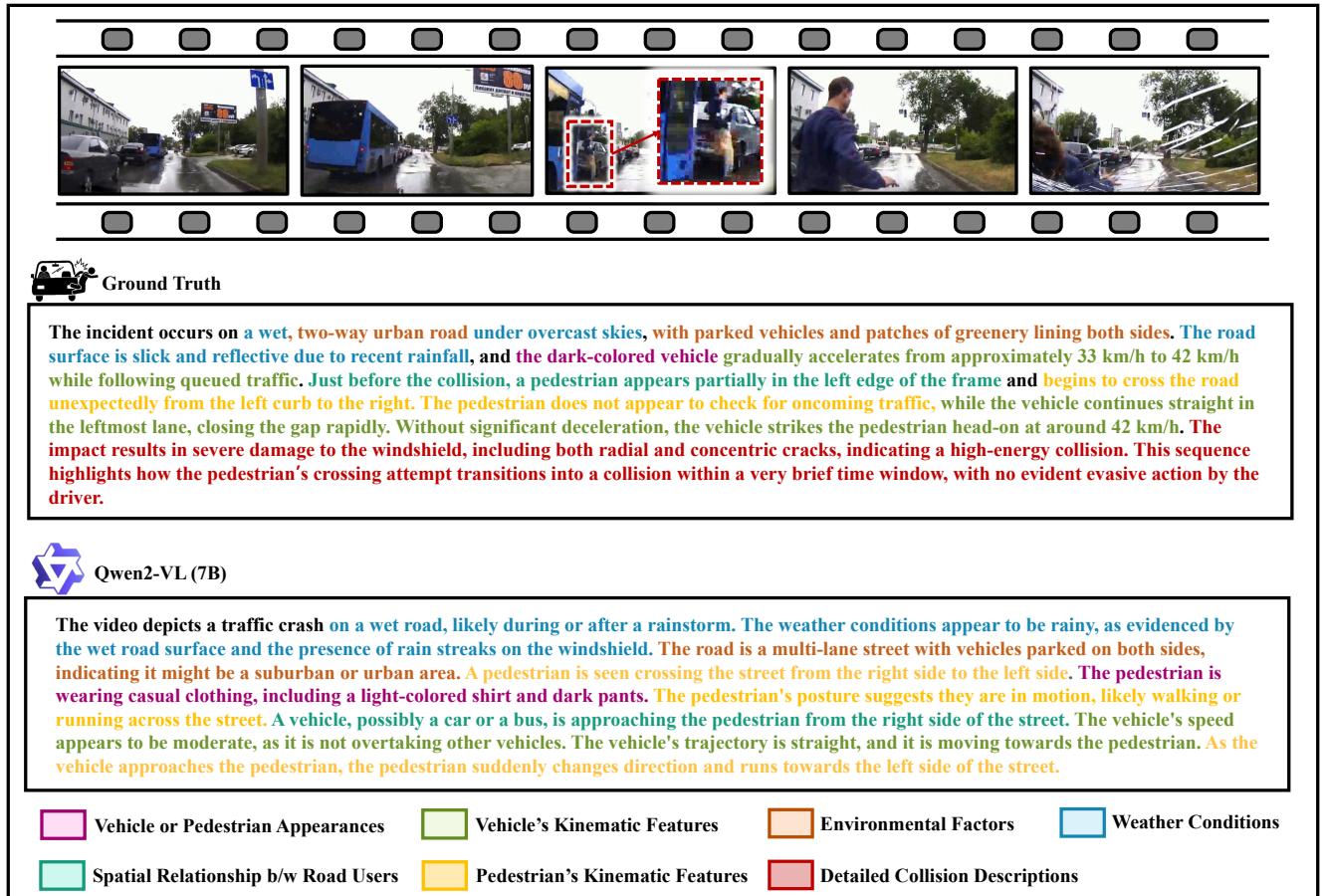


Figure 5. Accident description from both Ground Truth in VRU-Accident and Qwen2-VL(7B) which achieved the best performance in the dense captioning task. Please refer to Figure 9 in Supplementary Section C for descriptions generated from all MLLMs.

difficulty stems from the models’ inability to reliably distinguish between different types of accident agents. For instance, models frequently misclassify options when both a pedestrian and a cyclist are mentioned, or when they must differentiate between ego-vehicle and surrounding vehicles, indicating limitations in fine-grained object-level reasoning within accident contexts. Notably, performance in the ‘Accident Cause’ category is consistently poor across most models, with several falling below 30%, indicating that current MLLMs lack robust causal reasoning capabilities in safety-critical scenarios. Compared to human experts, who achieve over 94% accuracy in all categories, the gap highlights significant room for improvement in accident-centric understanding. These findings emphasize the importance of including causal and preventive questions in benchmarks for evaluating deeper vision-language reasoning, particularly in scenarios involving VRUs. The proposed VRU-Accident benchmark thus provides a challenging and diagnostic testbed for probing the limitations and capabilities of modern MLLMs in accident-related understanding.

To provide a holistic overview of model performance of VQA task, we visualize the results in Figure 4. This summary highlights the overall limitations of current MLLMs when applied to complex, safety-critical accident scenarios. Despite strong performance on certain visual attributes, most models struggle with causal reasoning and fine-grained collision understanding. These findings underscore the challenging nature of this benchmark and indicate substantial room for improvement in developing more robust and context-aware multimodal models.

**Dense Captioning Task.** Table 5 benchmarks 16 SOTA VLMs on SPICE, METEOR, COMET, and ROUGE. GPT-4 is excluded from this comparison, as it was used to generate the initial reference captions for the videos in the VRU\_Accident benchmark. Gemini 1.5-flash leads the leaderboard, recording 0.194 SPICE, 0.285 METEOR, and 0.741 COMET, together with the highest ROUGE-F values of 0.481 (R-1), 0.148 (R-2) and 0.266 (R-L). Compared with the best open-source VLM, Qwen2-VL (7B), Gemini has absolute gains of +0.024 SPICE, +0.020 COMET, +0.025 ROUGE-1 F, +0.014 ROUGE-2 F and +0.018 ROUGE-L F, while matching Qwen2-VL on METEOR. These margins show that Gemini extracts finer scene details and maintains better temporal coverage in complex accident videos. Among open-source VLMs, Qwen2-VL (7B) is the clear front-runner. It couples the highest open-source scores in METEOR (0.285) and COMET (0.721) with strong balance between precision and recall, delivering 0.456/0.134/0.248 ROUGE-F. When precision alone is considered, Video-XL2 (7B) edges ahead with 0.491 (R-1 P) and 0.266 (R-L P), yet its low recall (0.378 R-1) indicates it produces short captions that omit salient context. In contrast, InternVL3 (2B) delivers the weak-

est semantic quality (0.100 SPICE, 0.584 COMET) and the lowest ROUGE-F (0.345 R-1), suggesting fragmented, short descriptions. Mobile-VideoGPT (1.5B) also underperforms, posting the smallest ROUGE-1 precision (0.363) and ROUGE-L precision (0.180), consistent with captions that miss core entities and actions. Overall, Gemini 1.5-flash retains the lead across both the VQA and dense-caption tasks on VRU\_Accident. For open-source workflows, Qwen2-VL (7B) is the best choice for producing rich, spatiotemporal dynamics aware accident descriptions. *Overall*, although Gemini 1.5-flash and Qwen2-VL (7B) achieve high COMET score, their low SPICE, METEOR, and ROUGE-L scores reveal clear gaps in causal reasoning, spatial relation understanding and temporal coherence.

We present a qualitative comparison between the ground truth caption in VRU-Accident and the caption generated by Qwen2-VL(7B), the best-performing open-source model in the dense captioning task, as shown in Figure 5. Qwen2-VL(7B) captures key contextual elements, such as weather conditions, environmental layout, pedestrian appearances, and vehicle trajectories, which contributes to its strong overall performance across the evaluation metrics. However, despite these strengths, the model fails to describe critical details about the collision itself, an essential component in safety-critical scenarios, and even hallucinates the pedestrian’s motion, misrepresenting their crossing direction. This highlights the inherent challenge of the VRU-Accident benchmark, which requires not only general scene understanding but also fine-grained reasoning about spatiotemporal dynamics in accident scenarios.

## 5. Conclusion

This work presents VRU-Accident, the first large-scale vision-language benchmark specifically designed to evaluate multimodal large language models (MLLMs) in safety-critical scenarios involving VRUs. Our benchmark comprises 1K real-world traffic accident videos annotated with over 6K question-answer pairs and 1K dense descriptions, enabling fine-grained assessments of both causal reasoning and narrative generation in accident contexts. Through extensive evaluations of 17 state-of-the-art MLLMs, we found that while models perform well on visually grounded attributes, they struggle with high-level reasoning tasks such as accident causes, prevention measures, road configurations, and accident type identification. These limitations highlight the current models’ difficulty in interpreting dynamic and complex environmental cues, as well as distinguishing between fine-grained object roles in collision events. By offering both diagnostic and generative evaluation settings, VRU-Accident provides a unified and challenging testbed for advancing the capabilities of future multimodal systems in traffic safety domains.

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# Supplementary: VRU-Accident: A Vision-Language Benchmark for Video Question Answering and Dense Captioning for Accident Scene Understanding

## A. Supplementary Organization

We organize the supplementary material as follows:

- Section B: VRU-Accident Details
- Section C: Qualitative Examples
- Section D: Prompts for VRU-Accident Curation
- Section E: Reproduction of Experiment

## B. VRU-Accident Details

### B.1. Task-Specific Prompts

We present the input prompts used for MLLMs for each of the two tasks in VRU-Accident: VQA and Dense Captioning. The prompts are designed to elicit informative and structured responses from the models when paired with video inputs.

**Prompts for VQA task** For each question category in the VQA task, we provide a specific prompt. The prompts used are:

- **Weather and Light Condition:** What’s the weather and lighting? Choose the correct option (A, B, C, or D) without any explanations.
- **Traffic Environment:** Where did the accident happen? Choose the correct option (A, B, C, or D) without any explanations.
- **Road Configuration:** What type of road is shown? Choose the correct option (A, B, C, or D) without any explanations.
- **Accident Type:** What kind of accident occurred? Choose the correct option (A, B, C, or D) without any explanations.
- **Accident Cause:** Why did the accident happen? Choose the correct option (A, B, C, or D) without any explanations.
- **Accident Prevention Measure:** How could this accident be prevented? Choose the correct option (A, B, C, or D) without any explanations.

**Prompts for Dense Captioning task** To generate textual descriptions that match the level of detail and narrative style of the ground truth dense captions in VRU-Accident, we used the following prompt for all MLLMs:

- Provide a detailed description of this accident video. Use clear and complete sentences with appropriate traffic and accident-related terminology. Include descriptions of weather conditions, road type, and vehicle or pedestrian appearance (such as clothing and posture). Mention vehicle speed, trajectory, and movements, as well

as any changes in the pedestrian’s behavior. Focus on the dynamics of the collision, including vehicle approach, pedestrian movement, and final impact.

## B.2. Evaluation Metrics

In this section, we supplement explanation of evaluation metrics used for both VQA and Dense Captioning tasks in the main manuscript.

**VQA Evaluation Metrics** We evaluate the performance of models on the VQA task using standard classification accuracy per category. For each category  $j$ , we define the accuracy  $\text{Acc}_j$  as  $\text{Acc}_j = N_j^{\text{correct}} / N_j^{\text{total}}$  where  $N_j^{\text{correct}}$  denotes the number of correctly predicted samples, and  $N_j^{\text{total}}$  is the total number of samples for category  $j$ . Note that, unlike conventional classification tasks where a model selects from a fixed set of global class labels, each question  $q_j$  in our benchmark is associated with a dynamically constructed candidate set  $\hat{Y}_j$  that includes one correct answer and three counterfactual distractors. This makes the task more challenging, as models must perform fine-grained reasoning to distinguish the correct answer from contextually plausible but incorrect alternatives.

**Dense Captioning Evaluation Metrics** We select well-accepted and reliable metrics, including SPICE [6], METEOR [19], COMET [34], and ROUGE scores [22], to quantitatively evaluate the generated descriptions from the VLMs.

First of all, the SPICE metric evaluates caption quality by comparing semantic content in the form of tuples extracted from scene graphs. Each caption is parsed into a set of tuples representing objects, attributes, and relations. The SPICE F1 score is computed as the harmonic mean of tuple-level precision and recall:

$$\text{SPICE}_{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \quad (1)$$

where Precision and Recall are defined as:

$$\text{Precision} = \frac{|\mathcal{T}_{\text{gen}} \cap \mathcal{T}_{\text{ref}}|}{|\mathcal{T}_{\text{gen}}|}, \quad (2)$$

$$\text{Recall} = \frac{|\mathcal{T}_{\text{gen}} \cap \mathcal{T}_{\text{ref}}|}{|\mathcal{T}_{\text{ref}}|}, \quad (3)$$

with  $\mathcal{T}_{\text{gen}}$  and  $\mathcal{T}_{\text{ref}}$  denoting the sets of tuples from the generated and reference captions, respectively.

Secondly, METEOR captures both precision and recall of matching words, balancing linguistic precision and semantic recall. The METEOR score is calculated using the following formula:

$$\text{METEOR} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \alpha \times \text{Recall} + (1 - \alpha)} \quad (4)$$

Precision represents the proportion of words in the generated text that match the reference text, while Recall indicates the proportion of words in the reference text that are captured in the generated text. The parameter  $\alpha$  functions as a weighting factor, balancing linguistic precision and semantic recall to provide an adaptive evaluation of the generated text’s fidelity and coverage compared to the reference.

Thirdly, COMET is a neural-based metric that leverages pre-trained multilingual language models to predict human judgment scores for machine-generated text. Unlike surface-level metrics that rely solely on n-gram overlaps, COMET evaluates the semantic adequacy and fluency of the generated captions by comparing them against reference texts using contextual embeddings. Formally, COMET operates by encoding the source ( $S$ ), reference ( $R$ ), and hypothesis ( $H$ ) using a pre-trained model and passing them through a regression head to produce a quality score:

$$\text{COMET}(S, R, H) = f_\theta(\text{Enc}(S), \text{Enc}(R), \text{Enc}(H)) \quad (5)$$

where  $\text{Enc}(\cdot)$  denotes the encoder output from the language model and  $f_\theta$  represents the learned regression layer that maps the embeddings to a scalar score. COMET provides a more human-aligned assessment of caption quality, especially in capturing nuanced semantic differences that traditional metrics may overlook.

Finally, the ROUGE score is a set of metrics used to evaluate the summarization quality, specifically through precision (P), recall (R), and harmonic mean (F) scores based on n-gram overlaps. We report ROUGE-1, ROUGE-2, and ROUGE-L scores, corresponding to unigram overlap, bigram overlap, and longest common subsequence (LCS), respectively. For each variant, we compute precision, recall, and F1 as follows:

$$\text{Precision}_{\text{ROUGE}-n} = \frac{|\text{n-gram}_{\text{gen}} \cap \text{n-gram}_{\text{ref}}|}{|\text{n-gram}_{\text{gen}}|}, \quad (6)$$

$$\text{Recall}_{\text{ROUGE}-n} = \frac{|\text{n-gram}_{\text{gen}} \cap \text{n-gram}_{\text{ref}}|}{|\text{n-gram}_{\text{ref}}|}, \quad (7)$$

$$\text{F1}_{\text{ROUGE}-n} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \quad (8)$$

where  $n \in \{1, 2\}$  for ROUGE-1 and ROUGE-2, and  $\text{n-gram}_{\text{gen}}$ ,  $\text{n-gram}_{\text{ref}}$  denote the sets of n-grams in the generated and reference captions, respectively.

For ROUGE-L, which is based on the longest common subsequence (LCS), the scores are defined as:

$$\text{Precision}_{\text{ROUGE-L}} = \frac{\text{LCS}(\text{gen}, \text{ref})}{|\text{gen}|}, \quad (9)$$

$$\text{Recall}_{\text{ROUGE-L}} = \frac{\text{LCS}(\text{gen}, \text{ref})}{|\text{ref}|}, \quad (10)$$

$$\text{F1}_{\text{ROUGE-L}} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (11)$$

### B.3. Annotation Detail

Our VRU-Accident benchmark is designed to evaluate two core tasks: Video Question Answering (VQA) and Dense Captioning. The goal of the VQA task is to select the most appropriate answer from concise options—typically represented as short phrases a word, while the Dense Captioning task aims to generate detailed natural language descriptions that capture the full spatio-temporal context of a traffic accident. Given that real-world accident scenarios often involve complex and intertwined physical, environmental, and behavioral elements, it is inherently difficult to fully represent such events using concise options alone. Therefore, we provide annotation guidelines below that clarify how we determined the ground truth labels for each VQA category, while noting that richer, time-dependent contextual information is separately captured in the dense caption annotations.

**Weather & Light Condition** This category is annotated based on how the weather and lighting conditions plausibly contributed to the accident. For instance, if visibility is generally clear and there is no evidence of severe shadows or rain, the condition is annotated as a “sunny day” even if the sunlight appears diffused. Conversely, if the road surface appears wet or snow-covered—even in the absence of ongoing precipitation—we annotate the condition as “rainy” or “snowy” due to the increased risk of slipping and reduced friction. These decisions are made from a safety-critical perspective, prioritizing conditions that affect vehicle control or pedestrian stability. More detailed visual cues regarding surface wetness, lighting, or reflections are included in the dense caption descriptions.

**Traffic Environment** Accidents involving VRUs generally occur in either urban or rural settings. The environmental classification is relatively straightforward based on visual cues such as infrastructure density, type of roadside elements, and presence of intersections or buildings. In most cases, the classification is unambiguous.

**Road Configuration** Although many videos provide a clear view of the road structure, the moving dashcam per-

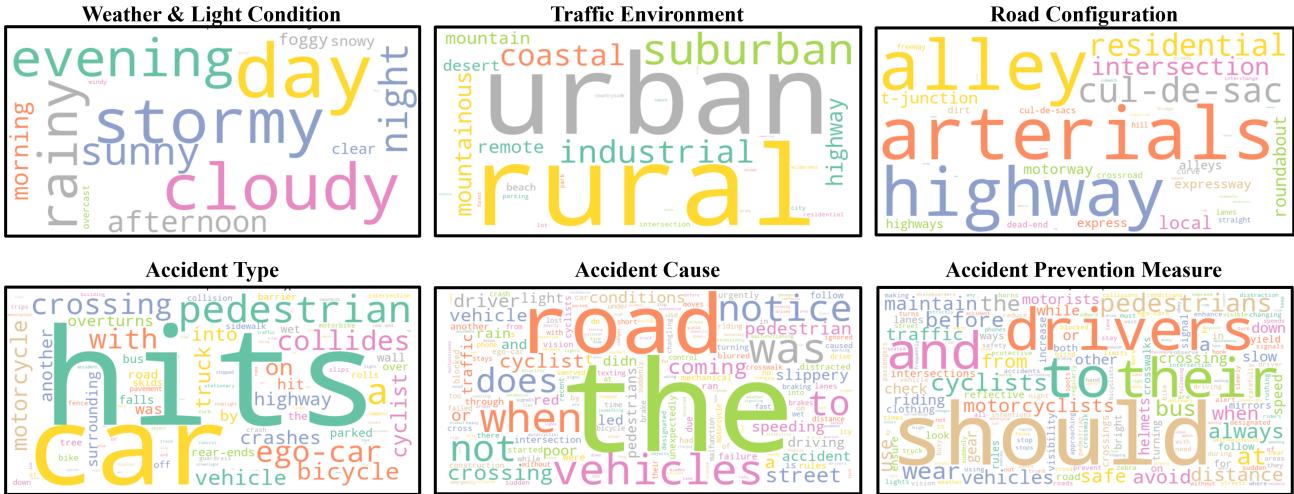


Figure 6. Word frequency per each category in the VRU-Accident benchmark.

spective can sometimes obscure precise location categorization. For example, if a vehicle is approaching an intersection, the same video segment may contain both arterial roads and the intersection itself. In such cases, we annotate the configuration based on where the key event (e.g., collision or near-miss) occurs. If the impact takes place just before entering the intersection, the label is set to “arterial road”; if the event occurs within the crossroad, it is labeled as “intersection.” The sequential progression and transitions in road context are described in detail within the dense captions.

**Accident Type** While most accident types can be clearly and concisely described (e.g., “car hits pedestrian,” “bicycle falls”), there are borderline or ambiguous cases. For instance, when a dashcam-equipped vehicle rapidly approaches a pedestrian and the pedestrian narrowly avoids contact by sidestepping, it becomes unclear whether to classify the event as an actual collision or a near-miss. In such cases, we annotate based on the interaction and directionality of the entities involved. If a pedestrian avoids a moving ego-vehicle by inches, the event is still annotated as “ego-car hits a pedestrian” for the sake of interpretability and consistency. Similarly, if a cyclist accidents into a parked vehicle, it is labeled as “car hits cyclist,” following common conventions seen in prior datasets such as [11, 12]. These nuances are captured more fully in the dense captions, where the dynamic unfolding of the scenario is described.

**Accident Cause** Causality in traffic accidents is often multi-factorial and temporally distributed. It is difficult to capture such complexity within a short answer choice.

Therefore, our annotations focus on the most immediate and visually interpretable cause of the accident—such as driver inattention, sudden lane change, or pedestrian jaywalking. These labels are selected based on high-salience cues that directly precede the event. The dense caption annotations, however, elaborate on the sequence of road user actions, delays in reaction, or misjudgments over time that contributed to the accident.

**Accident Prevention Measure** This category is annotated based on what preventive action could have reasonably avoided the accident, considering the behavior of all involved road users. Rather than speculating on counterfactuals involving unrealistic interventions, we focus on plausible, context-aware measures that align with traffic norms and human capabilities. For example, if a vehicle accelerated despite a pedestrian entering the crosswalk, the prevention measure might be “driver should yield to pedestrian.” In another case, if a cyclist riding without a helmet crosses the road illegally during rainy conditions and collides with a vehicle, the core cause of the accident is the illegal crossing. Among multiple plausible prevention strategies—such as “cyclist should wear a helmet,” “cyclist should wear bright clothing,” “cyclist should reduce speed,” and “cyclist should use designated crosswalk”—we annotate the most direct and effective preventive measure, in this case: “cyclist should use designated crosswalk.” This enables our benchmark to assess whether models can move beyond reliance on visually salient but potentially misleading cues, and instead demonstrate high-level understanding by identifying the true cause of the accident and articulating the most appropriate preventive action. In other words, it evaluates the model’s ability to reason about causality in

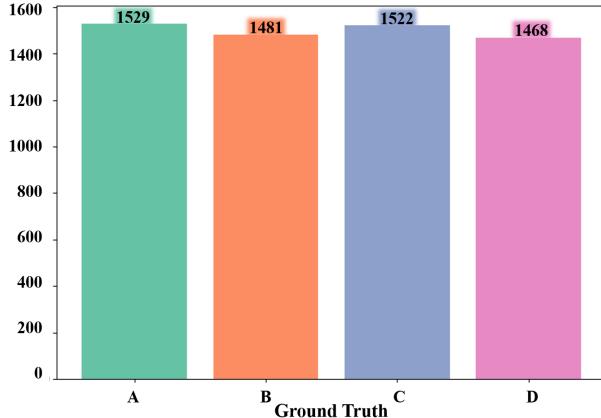


Figure 7. Distribution of ground truth of the VQA task in the VRU-Accident benchmark.

safety-critical scenarios rather than simply describing visually correct but contextually irrelevant information.

#### B.4. VQA Statistics

**Word Distribution per Category** As illustrated in Figure 6, the answer options across six VQA categories exhibit a wide range of lexical diversity. Each category—ranging from *Weather & Light Condition* to *Accident Prevention Measure*—contains semantically rich and diverse phrases. This diversity increases the difficulty of answer selection, requiring high-level scene understanding and contextual reasoning beyond keyword matching. Therefore, the benchmark provides a suitable evaluation setting for probing the generalization capability and multimodal grounding ability of MLLMs.

**Balanced Ground Truth Distribution** Figure 7 presents the overall distribution of ground truth answers (A–D) in the VRU-Accident benchmark. The distribution remains relatively balanced across all four options, with less than 5% deviation between the most and least frequent labels. This balance mitigates bias toward any specific answer index and ensures reliable evaluation without prior answer frequency bias, making the benchmark statistically robust for multi-choice classification tasks.

#### Semantic Similarity Between Question and Answers

To assess the semantic relevance between questions and answer options in VRU-Accident, we compute the cosine similarity between their embeddings using the all-MiniLM-L6-v2 model [51]. We denote the embedding model as a function  $F(\cdot)$ , which maps each sentence into a fixed-dimensional vector. For a given question  $q$  and its four answer options  $a_1, a_2, a_3, a_4$ , the cosine similarity between the question and each option is calculated as:

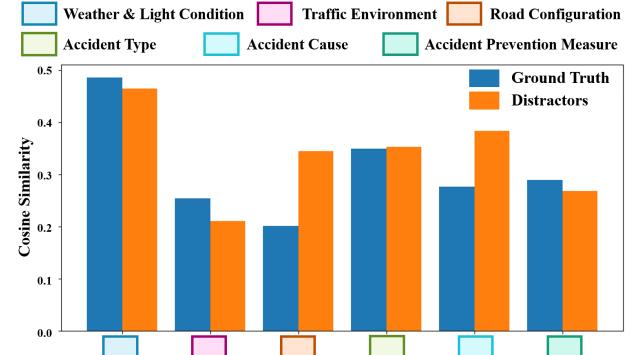


Figure 8. Comparison of average Q-A cosine similarity for ground truth answers and distractors across VQA categories in VRU-Accident benchmark.

$$\text{sim}(q, a_k) = \frac{\langle F(q), F(a_k) \rangle}{\|F(q)\| \cdot \|F(a_k)\|}, \quad (12)$$

where  $k \in \{1, 2, 3, 4\}$ . For each option  $k$ , we evaluate the average similarity of category  $j$  between the question and the ground truth answer over all  $N$  samples. This average ground truth similarity is computed as:

$$\text{Sim}_j^{\text{GT}} = \frac{1}{N} \sum_{i=1}^N \text{sim}(q^{(i)}, a_{g^{(i)}}^{(i)}), \quad (13)$$

where  $a_{g^{(i)}}^{(i)}$  is the ground truth answer for the  $i$ -th sample. To assess the relevance of distractors, we take the three incorrect options for each sample, compute their similarity to the question, and average them across the dataset:

$$\text{Sim}_j^{\text{Dist}} = \frac{1}{3N} \sum_{i=1}^N \sum_{\substack{k=1 \\ k \neq g^{(i)}}}^4 \text{sim}(q^{(i)}, a_k^{(i)}). \quad (14)$$

Figure 8 shows that distractors in several categories exhibit comparable or even higher similarity to the question than the ground truth. This demonstrates that the distractor options are semantically plausible and not easily distinguishable without detailed reasoning. Therefore, this benchmark poses a challenging evaluation setting for assessing the semantic discrimination and contextual understanding capabilities of multimodal large language models (MLLMs).

## C. Qualitative Examples

To further analyze model performance, we present qualitative comparisons between the ground truth annotations in VRU-Accident and the responses generated by state-of-the-art MLLMs [7, 8, 20, 21, 25, 36, 37, 40, 45, 54, 56] for both the VQA and dense captioning tasks. Figure 9 illustrates

a representative set of cases, offering insight into the models’ capabilities and limitations in understanding complex accident scenarios.

We observe that many models correctly identify basic visual attributes (e.g., rainy day or urban setting). However, several limitations remain evident. For instance, while dense captions often include fluent descriptions of the scene layout and pedestrian appearances, models frequently hallucinate motion trajectories or misattribute collision responsibility, especially in complex scenarios involving occlusion or sudden movements.

These examples underscore the value of VRU-Accident as a challenging benchmark. It not only requires visual recognition but also demands high-level temporal and causal reasoning. By contrasting ground truth annotations with model predictions, our qualitative analysis reveals both the current capabilities and the remaining gaps in modern MLLMs’ ability to comprehend and explain real-world accidents involving vulnerable road users.

## D. Prompts for VRU-Accident Curation

**Prompts for VQA Curation** Figure 10 illustrates the detailed prompt used to curate the VQA benchmark in VRU-Accident. Human annotators first reviewed each event video and manually labeled the correct answer for each reasoning category. Based on this ground truth and the corresponding question, GPT-4o was employed to generate three plausible but incorrect options (distractors) that preserve semantic relevance but differ from the correct answer. The example in Figure 10 involves a rainy-day accident where a pedestrian suddenly emerges from between parked vehicles, resulting in a collision. For the **Accident Reason** category, the ground truth is “C. The ego-car’s vision is blocked or blurred, and there is no time to brake.” GPT-4o generates the following distractors: “A. Poor road conditions led to the accident,” “B. The brakes failed unexpectedly during the drive,” and “D. A cyclist suddenly crossed the road.” Option A, while weather-related, is incorrect because the road condition was not the direct cause. Option B is wrong as the brakes were functioning, and D is incorrect since the involved road user was a pedestrian, not a cyclist. These semantically plausible yet incorrect choices help assess whether MLLMs can go beyond surface-level cues and demonstrate high-level causal reasoning.

**Prompts for Dense Caption Curation** Figure 11 shows the prompt used to curate dense accident descriptions. The prompt instructs the model to describe each accident video with detailed and coherent narratives, covering weather conditions, road type, vehicle and pedestrian appearances, vehicle dynamics (e.g., speed and trajectory), pedestrian behavior, spatial and temporal relationships among road users, and final collision outcomes. GPT-4o takes the input video

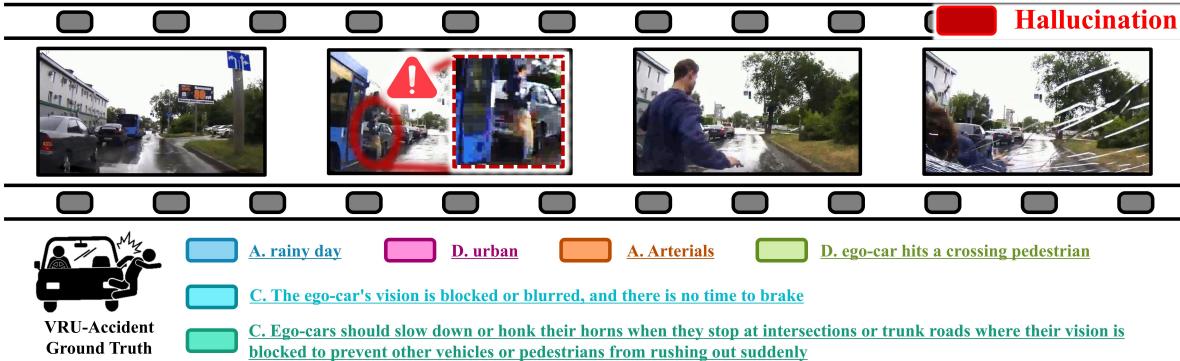
and prompt rules to generate a single paragraph that mirrors the descriptive style and level of detail found in human-written annotations. This design ensures that the generated captions are not only visually grounded but also demonstrate temporal reasoning and contextual understanding of the accident dynamics. As a result, the VRU-Accident benchmark enables qualitative assessment of MLLMs’ ability to comprehend and articulate complex accident scenarios beyond mere visual recognition.

## E. Reproduction of Experiment

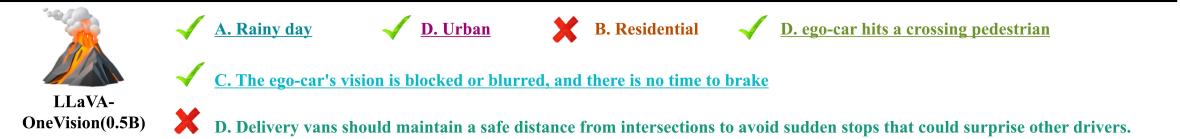
To encourage widespread use of our VRU-Accident benchmark and to support reproducibility of our experiments, we release all necessary resources used for all experiments in the main manuscript. This includes the inference scripts, model outputs, and evaluation results. Please visit our Github<sup>1</sup> and refer the **ReadMe** file for reproduction.

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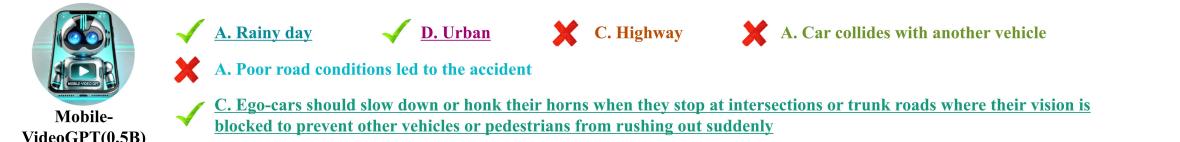
<sup>1</sup><https://github.com/Kimyounggun99/VRU-Accident>



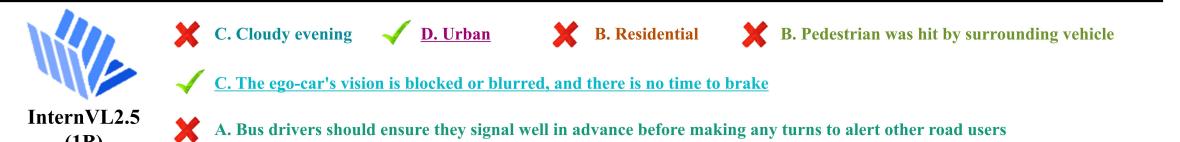
The incident occurs on a wet, two-way urban road under overcast skies, with parked vehicles and patches of greenery lining both sides. The road surface is slick and reflective due to recent rainfall, and the dark-colored vehicle gradually accelerates from approximately 33 km/h to 42 km/h while following queued traffic. Just before the collision, a pedestrian appears partially in the left edge of the frame and begins to cross the road unexpectedly from the left curb to the right. The pedestrian does not appear to check for oncoming traffic, while the vehicle continues straight in the leftmost lane, closing the gap rapidly. Without significant deceleration, the vehicle strikes the pedestrian head-on at around 42 km/h. The impact results in severe damage to the windshield, including both radial and concentric cracks, indicating a high-energy collision. This sequence highlights how the pedestrian's crossing attempt transitions into a collision within a very brief time window, with no evident evasive action by the driver.



The video captures a moment of a car accident on a wet road. The scene is set in a residential area with buildings on one side and a road on the other. The sky is overcast, and the road is slick with rain, reflecting the surrounding environment. The car in the foreground is a blue bus, and it is approaching a pedestrian crossing. The pedestrian, dressed in dark clothing, is crossing the road, and the car is making a sharp turn to avoid hitting the pedestrian. The pedestrian appears to be in a hurry, as indicated by their posture and the fact that they are crossing the road. (The car is making ... [repeating])



The blue bus was seen driving on the road with a sign that read 20% OFF. The driver of the bus then turned to the right and passed by a white car, which is parked in front of the bus.



The video captures an interaction between a vehicle and a pedestrian at a wet street intersection, characterized by a sense of urgency and motion. Initially, the scene is shot from a vehicle's dashboard camera, showing a wet pavement and adjacent buildings. The weather is overcast, with grey skies contributing to a somber mood. The scene then shifts to show pedestrians, with one crossing the street while being caught by the moving vehicle. The speedometer reads 38 km/h; this implies a moderate collision. The vehicle successfully avoids a potential hit before the pedestrian stumbles and tumbles over the windshield due to the speed of the vehicle chasing the pedestrian, eventually losing visibility and moving the camera away from the scene. The windshield is cracked, suggesting the force of impact.



Mobile-  
VideoGPT(1.5B)

- ✓ A. Rainy day ✓ D. Urban ✗ D. Alley ✓ D. ego-car hits a crossing pedestrian  
✓ C. The ego-car's vision is blocked or blurred, and there is no time to brake  
✓ C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly

The video captures a sequence of events unfolding on an overcast day, starting with a view from inside a vehicle moving through a rainy urban environment. Initially, the scene is set with raindrops visible on the windshield and various vehicles including a blue bus ahead, parked cars, and a white van in the background. The road appears wet, suggesting recent or ongoing rainfall. As the video progresses, there's minimal change initially; the rain continues to fall steadily, and the vehicles maintain their positions relative to each other, indicating slow movement or a stop at a traffic light. A new element introduced is a signboard displaying "80" which could be interpreted as speed limits or directions, but its significance remains unclear due to the lack of context. Further into the video, the camera angle shifts slightly, revealing more details such as a pedestrian crossing the street and a red car entering the frame, hinting at possible stops or changes in traffic signals. Despite these slight movements, the overall scene remains largely unchanged except



InternVL3 (2B)

- ✓ A. Rainy day ✓ D. Urban ✗ B. Residential ✓ D. ego-car hits a crossing pedestrian  
✓ C. The ego-car's vision is blocked or blurred, and there is no time to brake  
✗ B. Motorcyclists should wear reflective vests at night to enhance their visibility to other vehicles on the road.

The video shows a white car moving from the right side of the frame and coming up towards a blue trolley bus. The car collides with the bus, causing the glass to become shattered. The blue trolley bus crosses from the left side of the frame towards the right and comes to a stop. A person wearing a blue jacket and beige pants crosses the road from right to left. The camera is the driver's point of view. The road has green trees on the left; and a pole and grass on the right. Vehicles are driving on the road, and the weather is sunny, and it is raining. The speed is km per hour in the first frame, and the speed is km per hour at the end of the video. The license plate is seen on the first car and on the bus.



Qwen2.5-VL(3B)

- ✓ A. Rainy day ✓ D. Urban ✗ B. Residential ✓ D. ego-car hits a crossing pedestrian  
✗ D. A cyclist suddenly crossed the road  
✓ C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly

The video captures a sequence of events involving a bus and a pedestrian on a wet urban street. The scene is set during daylight hours, with overcast skies suggesting recent rain. The road appears to be a two-lane street with moderate traffic, including several cars and a blue bus. Initially, the bus is seen approaching from the left side of the frame, moving at a moderate speed indicated by the speedometer reading 35 km/h. The bus is a standard city bus, painted in blue and white, with visible advertisements on its side. As it approaches the pedestrian crossing, it slows down slightly, maintaining a speed of around 40 km/h. A pedestrian, dressed in casual attire, is seen crossing the street from the right side of the frame towards the left. The pedestrian appears to be in motion, possibly walking briskly, given the slight blur of their figure. The sidewalk is lined with trees and parked cars, contributing to a typical urban environment. As the bus continues its



Video-XL-Pro(3B)

- ✓ A. Rainy day ✓ D. Urban ✗ B. Residential ✓ D. ego-car hits a crossing pedestrian  
✓ C. The ego-car's vision is blocked or blurred, and there is no time to brake

- ✗ A. Bus drivers should ensure they signal well in advance before making any turns to alert other road users

The video captures a sequence of events on a rainy day in an urban setting, focusing on a street intersection. Initially, the scene is set with a wet road reflecting the overcast sky, and several vehicles are parked along the curb, including a blue bus and a black car. The background features buildings with green accents and a sign indicating "Park City" and a speed limit of 80 km/h. The timestamp reads "2019/07/08 03:28:25," and the camera's position suggests it is mounted inside a vehicle. As the video progresses, the blue bus begins to move forward, while the black car remains stationary. The bus approaches the intersection, and a pedestrian wearing dark clothing is seen crossing the street from right to left. The pedestrian appears to be in motion, possibly walking or running across the road. The camera angle shifts slightly to follow the bus as it moves closer to the intersection, capturing the pedestrian's movement more



InternVL2.5 (4B)

- ✓ A. Rainy day    ✓ D. Urban    ✗ B. Residential    ✓ D. ego-car hits a crossing pedestrian
- ✓ C. The ego-car's vision is blocked or blurred, and there is no time to brake
- ✗ A. Bus drivers should ensure they signal well in advance before making any turns to alert other road users

The video presents an indoor shooting environment, starting with multiple gunshots and showing smoke emanating from various firearm calibers. It then transitions to an outdoor urban scene. The video begins indoors with smoke visible, possibly from firearms, transitioning into an outdoor scene on a rainy day. The road appears wet, with reflections on the pavement. The surroundings include buildings and greenery along the side of the road. A person in a blue jacket and jeans is observed crossing the road in front of a blue bus. Another pedestrian, wearing dark pants and brown shoes, is also seen crossing the road. Traffic conditions are observed on a multi-lane road typical of cities, with vehicles traveling in various directions. The pedestrian then moves further across the road near parked vehicles in a busy urban setting. The footage captures a moment of a pedestrian crossing in the roadway as vehicles pass by.



Video-XL2 (7B)

- ✓ A. Rainy day    ✓ D. Urban    ✗ B. Residential    ✓ D. ego-car hits a crossing pedestrian
- ✗ D. A cyclist suddenly crossed the road
- ✗ A. Bus drivers should ensure they signal well in advance before making any turns to alert other road users

The video clip shows a first-person perspective from inside a vehicle, likely an ambulance given the title reference to 'CMC' (ambulance). The timestamp indicates it's early morning. The environment is urban with wet roads suggesting recent rain. A blue bus and various cars are parked along the street. A pedestrian in dark clothing suddenly crosses the road from right to left, seemingly unaware of oncoming traffic. The vehicle approaches at speed, indicated by the timestamp and speedometer reading 40 km/h. As the vehicle gets closer, the pedestrian is hit, causing a loud impact sound. The camera shakes violently, and the windshield cracks, obscuring the view momentarily. The pedestrian falls to the ground, and the vehicle comes to a stop. The colors are muted due to overcast weather, with grey dominating the scene.

LLaVA-Next-Video  
(7B)

- ✓ A. Rainy day    ✓ D. Urban    ✓ A. Arterials    ✗ A. Car collides with another vehicle
- ✗ A. Poor road conditions led to the accident
- ✗ A. Bus drivers should ensure they signal well in advance before making any turns to alert other road users

The video depicts a car crash that occurred in a city street on a rainy day. The scene is captured from the perspective of a car's dashboard camera, showing a blue car driving down the street. The car is moving at a moderate speed, and the driver is wearing a black jacket and appears to be focused on the road ahead. As the car approaches a pedestrian crossing, the pedestrian suddenly steps onto the road, seemingly without looking for oncoming traffic. The driver of the blue car brakes abruptly to avoid a collision, but the pedestrian does not move out of the way in time, resulting in a head-on collision. The impact is severe, causing the pedestrian to fall onto the road. The car's trajectory is altered by the collision, and the driver's attention is drawn to the pedestrian's sudden appearance. The weather conditions are rainy, which may



Qwen2-VL(7B)

- ✓ A. Rainy day    ✓ D. Urban    ✗ B. Residential    ✓ D. ego-car hits a crossing pedestrian
- ✓ C. The ego-car's vision is blocked or blurred, and there is no time to brake
- ✗ A. Bus drivers should ensure they signal well in advance before making any turns to alert other road users

The video depicts a traffic crash on a wet road, likely during or after a rainstorm. The weather conditions appear to be rainy, as evidenced by the wet road surface and the presence of rain streaks on the windshield. The road is a multi-lane street with vehicles parked on both sides, indicating it might be a suburban or urban area. A pedestrian is seen crossing the street from the right side to the left side. The pedestrian is wearing casual clothing, including a light-colored shirt and dark pants. The pedestrian's posture suggests they are in motion, likely walking or running across the street. A vehicle, possibly a car or a bus, is approaching the pedestrian from the right side of the street. The vehicle's speed appears to be moderate, as it is not overtaking other vehicles. The vehicle's trajectory is straight, and it is moving towards the pedestrian. As the vehicle approaches the pedestrian, the pedestrian suddenly changes direction and runs towards the left side of the street. This sudden change



LLaVA-Video (7B)

- |   |  |  |
|---|--|--|
| <span style="color: green;">✓</span> A. Rainy day<br><span style="color: green;">✓</span> C. The ego-car's vision is blocked or blurred, and there is no time to brake<br><span style="color: green;">✓</span> C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly | <span style="color: green;">✓</span> D. Urban<br><span style="color: red;">✗</span> B. Residential | <span style="color: green;">✓</span> D. ego-car hits a crossing pedestrian |
|---|--|--|

The video begins with a view from inside a vehicle, showing a wet road with several cars ahead. The timestamp on the screen reads "2015/07/08 08:37:25" and the location is indicated as "ParkCity." The road appears to be in an urban area with buildings on the left and parked cars on the right. A billboard with text in Russian is visible on the right side of the road, indicating some form of advertisement or information for drivers. As the vehicle moves forward, it approaches a blue bus that is stopped in front of it. The bus is large and has a dark blue color. The vehicle continues to move forward, and the bus remains stationary. Suddenly, a pedestrian wearing a blue jacket and beige pants appears in the frame, crossing the road from left to right. The pedestrian is in motion, and the vehicle's speed is not clearly visible due to the camera angle. The pedestrian continues to cross the road,



InternVL2(8B)

- |   |  |   |
|---|--|---|
| <span style="color: green;">✓</span> A. Rainy day<br><span style="color: green;">✓</span> C. The ego-car's vision is blocked or blurred, and there is no time to brake<br><span style="color: green;">✓</span> C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly | <span style="color: green;">✓</span> D. Urban<br><span style="color: red;">✗</span> B. Residential | <span style="color: red;">✗</span> C. motorcycle skids off the road |
|---|--|---|

The video begins showing a typical urban street setting. A clear sky with no apparent wet conditions indicates dusk with dim ambient light and a mixture of shadows and faint illumination. Vehicles of various models and sizes are parked along both sides of the street, with a white SUV near the forefront. Trees on the right side offer a natural boundary to the scene adding a touch of greenery against the backdrop of buildings on the left. In the middle of the street, a light blue bus drives at a moderate speed in the opposite direction from the camera's view. As the bus continues down the road, another large structure in the distance is visible, indicating an urban environment. The presence of a pedestrian is noted walking upright along the sidewalk on the left side of the street, in mid-walk, suggesting they are not yet in immediate proximity to any vehicles. However, as the bus navigates down the wet street, the wet pavement reflects the light and captures a significant change—a vehicle approaching rapidly and



InternVL2.5(8B)

- |   |  |  |
|---|--|--|
| <span style="color: green;">✓</span> A. Rainy day<br><span style="color: green;">✓</span> C. The ego-car's vision is blocked or blurred, and there is no time to brake<br><span style="color: green;">✓</span> C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly | <span style="color: green;">✓</span> D. Urban<br><span style="color: red;">✗</span> B. Residential | <span style="color: green;">✓</span> D. ego-car hits a crossing pedestrian |
|---|--|--|

This dashcam footage captures an urban driving situation where a bus is stopped in traffic on a city street. The road appears wet from recent rain, reflecting the light and creating a slick surface. The bus, white with blue lower panels, is positioned perpendicular to the camera vehicle's trajectory. Initially, the bus is stopped, likely due to the traffic ahead, as vehicles line up closely behind it. To the right of the bus, a few cars are parked along the side of the road, and trees and buildings add to the city environment. In a sudden motion, the video captures a pedestrian in dark clothing and a backpack crossing the street from the right to the left. The individual runs, suggesting a possible urgency or an emergency, and appears to be attempting to cross despite oncoming traffic. The pedestrian has about halfway across the road when the collision occurs. An object, likely a piece of debris, or a rock, strikes the windshield in mid-motion, creating multiple impact



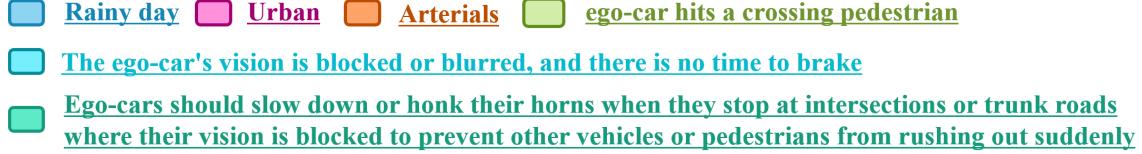
InternVL3(8B)

- |   |  |  |
|---|--|--|
| <span style="color: green;">✓</span> A. Rainy day<br><span style="color: red;">✗</span> D. A cyclist suddenly crossed the road<br><span style="color: green;">✓</span> C. Ego-cars should slow down or honk their horns when they stop at intersections or trunk roads where their vision is blocked to prevent other vehicles or pedestrians from rushing out suddenly | <span style="color: green;">✓</span> D. Urban<br><span style="color: red;">✗</span> B. Residential | <span style="color: green;">✓</span> D. ego-car hits a crossing pedestrian |
|---|--|--|

In the video, a vehicle approaching an intersection navigates past multiple parked cars on the left and a blue bus. The scene is set on a rain-slicked road, suggesting overcast weather conditions that reflect off the wet surface. As the vehicle continues moving forward, it passes by a series of parked cars aligned on the left side. The pedestrian, wearing dark clothing and pants, steps out from behind one of the parked cars. As the vehicle continues to advance, the pedestrian begins to move forward into the path's path trajectory. The vehicle maintains a moderate speed of around 40 km/h as it navigates the damp intersection. The pedestrian, appearing unaware or unattending to the approaching vehicle, steps directly into the travel path's path, resulting in a collision. The impact of the vehicle against the pedestrian is forceful, pushing the pedestrian's body against the vehicle's hood and windshield. Notably, the windshield is visibly fractured from the impact, indicating the severity of the collision. The

Figure 9. Qualitative comparison of VQA and dense captioning outputs from MLLMs on the VRU-Accident benchmark. Each example shows the ground truth annotation (top row) and the responses from models.



**<System>** 

You are creating a multiple-choice visual question answering (VQA) benchmark. 

**Question:** Why did the accident happen?  
**Correct Answer:** [The ego-car's vision is blocked or blurred, and there is no time to brake](#)

Your task is to generate \*\*three plausible but incorrect options\*\* (distractors) for this question. These distractors should:

# Rules  
 1. Be semantically relevant to the question, 2. Clearly incorrect (not matching the correct answer),  
 3. Diverse from one another, 4. Follow below rules to construct incorrect options.

# Rules  
 1. **Weather and Light:** Keep each distractor short and composed of two words (weather + lighting), similar to the correct answer.,  
 2. **Location:** Each distractor should be a single word describing a different plausible location.,  
 3. **Road Type:** Each distractor should be a single word referring to another type of road.,  
 4. **Accident Type:** Each distractor should be a short sentence, 3–7 words long, that describes a different but realistic accident.,  
 5. **Accident Reason:** Each distractor should be a short sentence, around 7–10 words, suggesting a different cause of accident.,  
 6. **Prevention Method:** Each distractor should be a full sentence, roughly similar in length and tone to the correct answer, but describing a different preventive strategy.

Now generate the distractors.

**<Output>** 

  
**VRU-Accident VQA Benchmark**

A. Poor road conditions led to the accident ✗  
 B. The brakes failed unexpectedly during the drive ✗  
 C. [The ego-car's vision is blocked or blurred, and there is no time to brake](#) ✓  
 D. A cyclist suddenly crossed the road ✗



Figure 10. Prompt used for curating VRU-Accident VQA benchmark, including category-specific rules and a generated multiple-choice question with one correct answer and three semantically plausible distractors.



## <System>



You are creating dense captions describing the video by following below rules.

### # Rules

1. Provide a detailed and precise description of this crash video in a single, concise paragraph.
2. Use clear, complete sentences, formal English with appropriate traffic and crash-related terminology.
3. Include descriptions of **weather conditions**, **road type**, and **vehicle or pedestrian appearance** (such as clothing and posture).
4. Mention **vehicle speed**, **trajectory**, and **movements**, as well as **any changes in the pedestrian's behavior and movements**.
5. Focus on the **dynamics of the collision**, including **vehicle approach**, **pedestrian movement**, and **final impact**.
6. Ensure the description captures **the sequence of events**, **their spatial relationships**, and is suitable as accurate ground truth data.
7. Please follow the style and level of detail of the following example:  
\n\n

### [Example]

- The pedestrian, a male in his 30s wearing a brown jacket and navy blue slacks, stands still on a two-way residential road with a dry and level asphalt surface and no sidewalks.
- Positioned diagonally to the left in front of the vehicle, he faces the same direction as the vehicle on this clear and bright day with usual traffic volume.
- The vehicle, traveling straight ahead at 20 km/h, moves from a far to near distance behind and to the right of the pedestrian, who is mostly unaware of the vehicle.
- As the vehicle's field of view begins to include the pedestrian, he slowly rushes out toward the right. Despite the calm surroundings, the vehicle collides with the pedestrian, concluding the scene.

## <Output>



The incident occurs on a wet, two-way urban road under overcast skies, with parked vehicles and patches of greenery lining both sides. The road surface is slick and reflective due to recent rainfall, and the dark-colored vehicle gradually accelerates from approximately 33 km/h to 42 km/h while following queued traffic. Just before the collision, a pedestrian appears partially in the left edge of the frame and begins to cross the road unexpectedly from the left curb to the right. The pedestrian does not appear to check for oncoming traffic, while the vehicle continues straight in the leftmost lane, closing the gap rapidly. Without significant deceleration, the vehicle strikes the pedestrian head-on at around 42 km/h. The impact results in severe damage to the windshield, including both radial and concentric cracks, indicating a high-energy collision. This sequence highlights how the pedestrian's crossing attempt transitions into a collision within a very brief time window, with no evident evasive action by the driver.

Figure 11. Prompt used for curating dense caption annotations in VRU-Accident. The prompt guides the model to describe accident videos with detailed references to weather, road configuration, agent appearance, kinematic features, and collision dynamics.