Anomaly Detection in the Era of Multimodal Large Language Models

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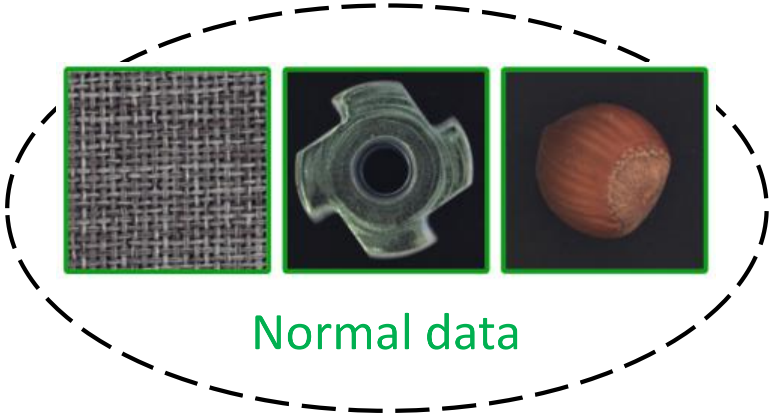
About Me

- Research Scientist @ **Honda Research Institute USA**
  San Jose, CA (2023 - Present)
- Research Intern @ **Amazon**
  Seattle, WA (Summer 2021 & 2022)

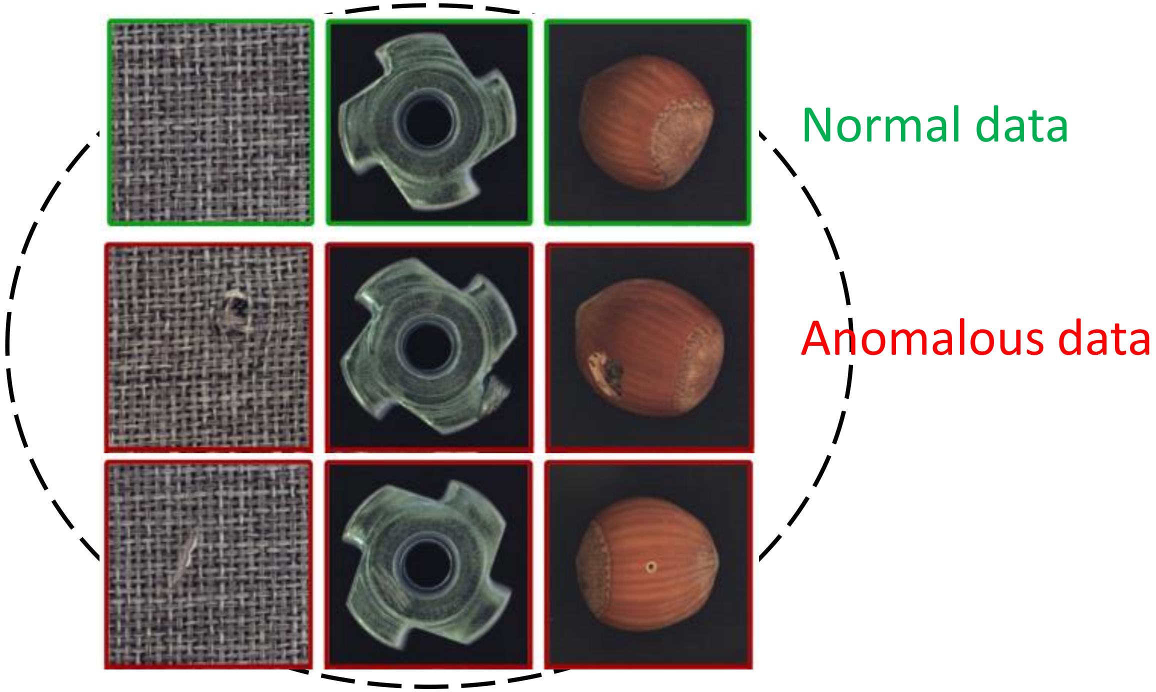
- PhD in ECE @ **Johns Hopkins University**
  Baltimore, MD (2019 - 2023)
- MS in EE @ **National Chiao Tung University**
  Taiwan (2017 - 2019)
- BS in EECS @ **National Chiao Tung University**
  Taiwan (2013 - 2017)

What is Anomaly Detection?

- **Problem definition**: An AD model is exclusively trained with **normal** data and is asked to identify whether a query example is **normal** or **anomalous**.
- **Motivation**: Anomalies are often rare and long-tailed, so they are costly to collect.
- Example:
  - **Normal data**: Flawless objects
  - **Anomalous data**: Defects



Training set



Test set

Image source:
[Bergmann et al. CVPR'19]

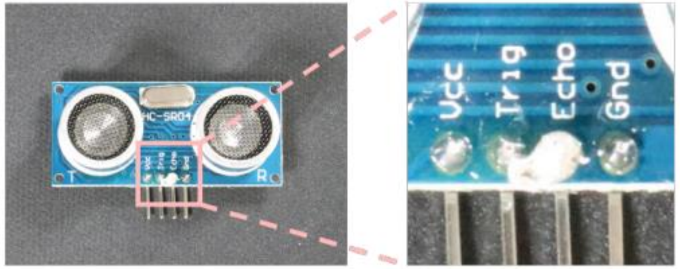
Visual Anomaly Detection: Images and Videos

- Visual AD is a long-established problem in computer vision.
- Given its practical significance, AD has been widely deployed in various applications.

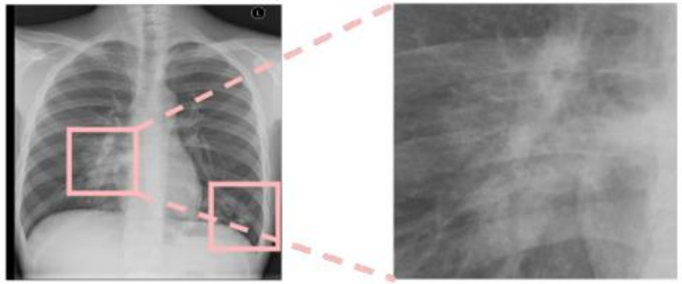
Video Anomaly Detection (VAD)

Security surveillance

Image Anomaly Detection (IAD)



Industrial image inspection

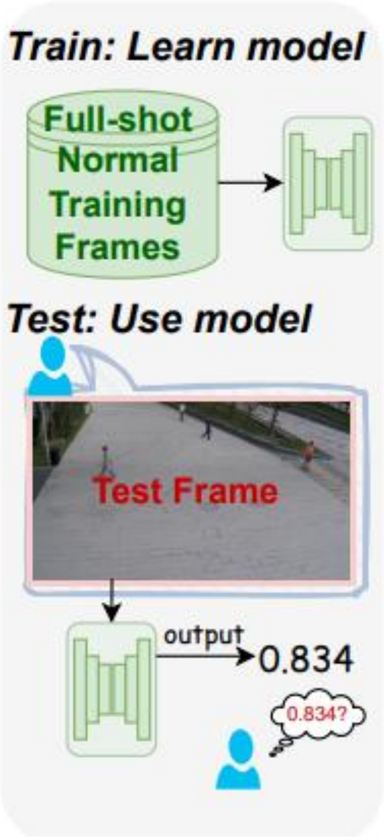


Medical image diagnosis

Image source: [Bergmann et al. CVPR’19] [Bao et al. CVPR’24] [Liu et al. CVPR’18]

Conventional Learning-based AD Approaches

- **Full-shot training**: An AD model is trained by a large amount of normal data to learn normal patterns
- **Output format**: Anomaly scores -> Thresholding
- **Metrics**: AUROC (area under ROC curve)



The Era of Multimodal Large Language Models

ChatGPT

Claude

deepseek

InternVL

MISTRAL AI_

Gemini

Qwen-VL

Anomaly Detection in the Era of MLLMs

How can AD benefit from MLLMs?

What breakthroughs can MLLMs bring to this long-established vision problem?

Anomaly Detection in the Era of MLLMs

	Conventional		MLLMs
How to learn	Full-shot training	→	Few-shot / Zero-shot
What to output	Detection only (anomaly scores)	→	Detection + Reasoning

Few-shot / Zero-shot:

- Prompting pipelines
- Model adaptability

Detection + Reasoning:

- Instruction tuning data
- New metrics
- New benchmarks

Anomaly Detection in the Era of MLLMs

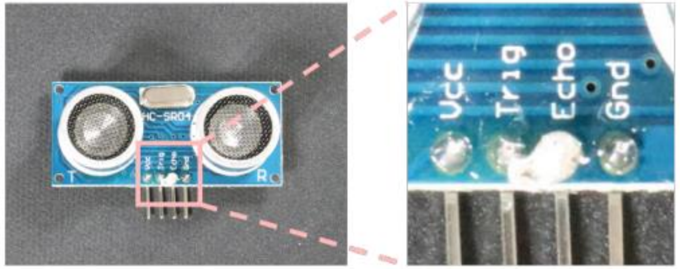
ECCV 2024

CVPR 2025

Video Anomaly Detection (VAD)

Security surveillance

Image Anomaly Detection (IAD)



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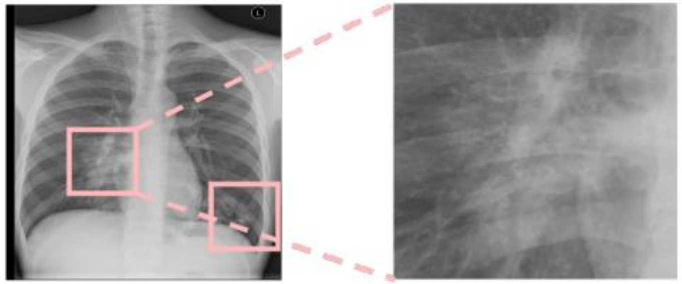

Medical image diagnosis

Image source: [Bergmann et al. CVPR'19] [Bao et al. CVPR'24] [Liu et al. CVPR'18]

Follow the Rules: Reasoning for Video Anomaly Detection with Large Language Models

Yuchen Yang[1*], Kwonjoon Lee[2], Behzad Dariush[2], Yinzhi Cao[1], and Shao-Yuan Lo[2]

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ECCV 2024

- One of the **first reasoning** methods for VAD
  - => Explain why normal/anomaly
- One of the **first few-shot prompting** methods for VAD
  - => Fast adaption to different definitions of “anomaly” for different applications

Problem Statement

- **Assumption**: We only have a few **normal** data for our specific application, and it's costly to collect **anomaly** data.
- **Challenge**: The definition of "**anomaly**" **depends on different context and downstream applications**.
- **Goal**: Develop a VAD model for our specific application (specific definition of "**normal**" & "**anomaly**") and explain the detection results.

person jogging versus person running outside a bank.

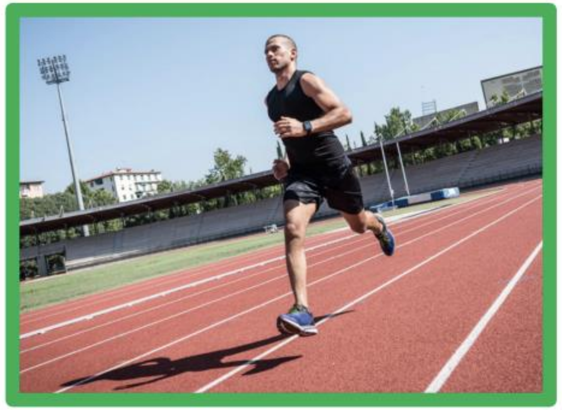
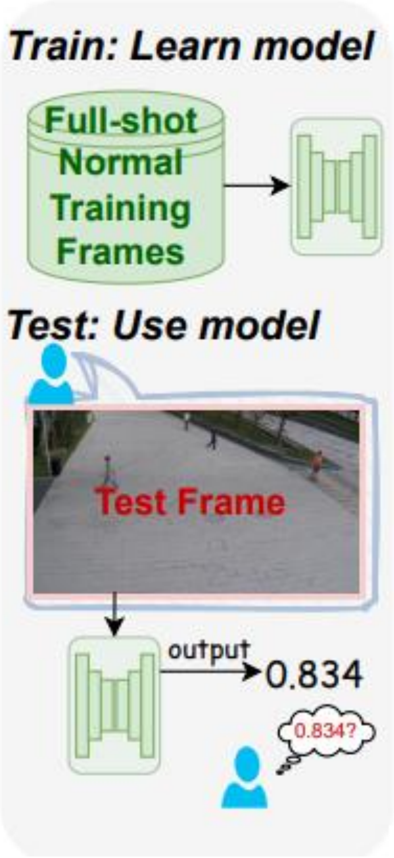


Image source: [Radu Tudor Ionescu. CVPR'23 Tutorial]

Conventional Learning-based Approaches

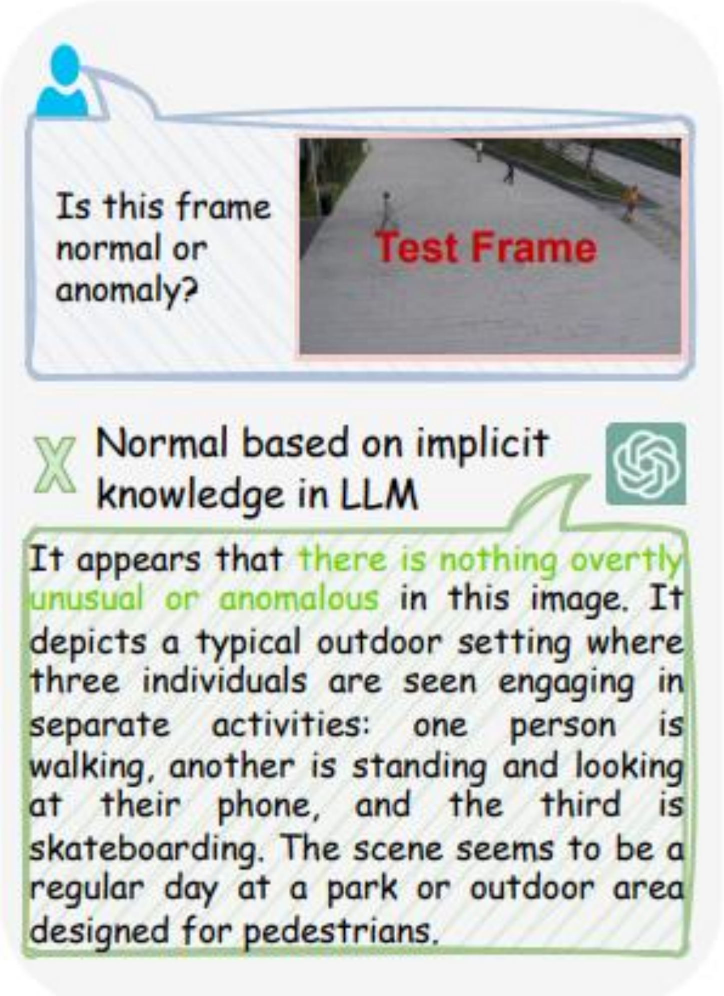
- **Full-shot training**: A VAD model is trained by a large amount of normal data to learning normal patterns
- **Output format**: Anomaly scores -> Thresholding
- **Metrics**: AUROC (area under ROC curve)



Query MLLMs Directly

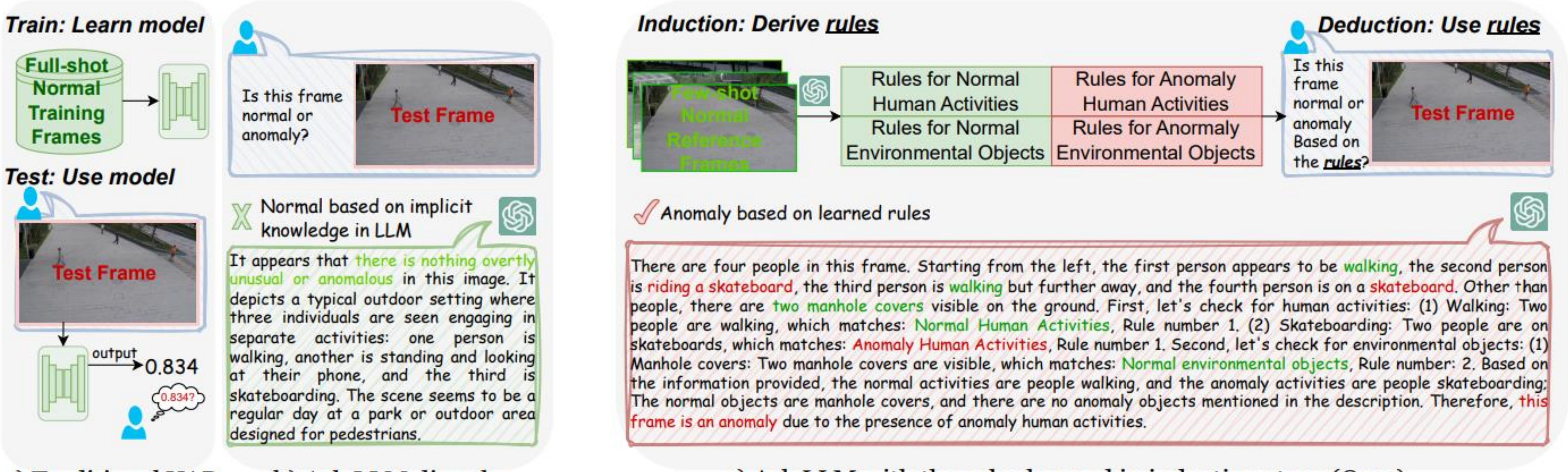
- The implicit knowledge pre-trained in MLLMs may not align with specific VAD needs.

- Here GPT-4V mistakenly treats "skateboarding" as normal.



Method

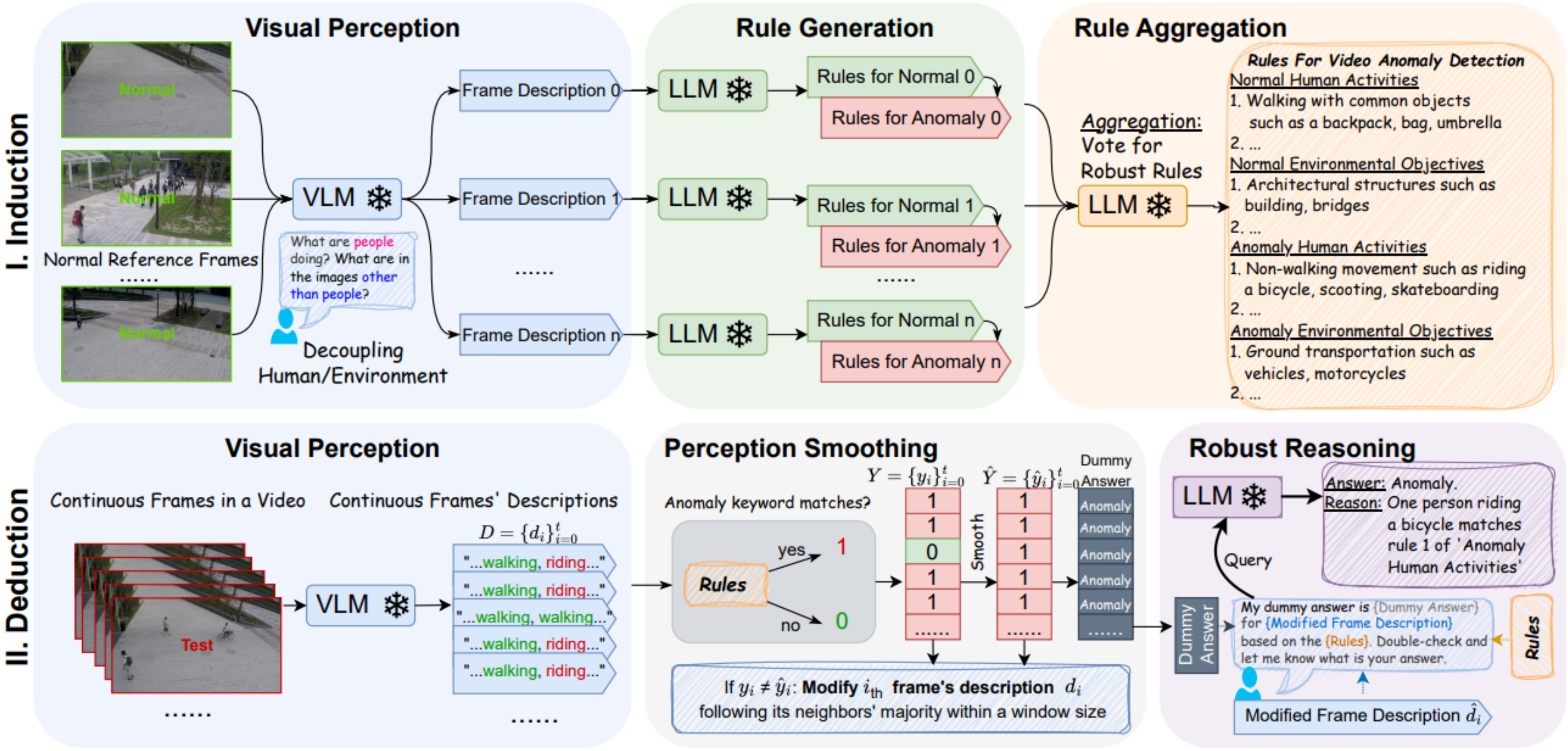
- **Induction**: Learn rules from few-shot normal reference frames
  - Few-normal shot prompting (no training needed)
- **Deduction**: Detect anomalies based on the rules
  - Correctly identifying "skateboarding" as an anomaly



a) Traditional VAD b) Ask LLM directly c) Ask LLM with the rules learned in induction stage (Ours)

Method

- **Induction (derive rules)**: Use the **few** available normal data as references to derive a set of rules. **Prompting** method without model weight training.
- **Deduction (inference)**: Perform VAD and **explain** detection results according to the induced rules.



Comparison with Conventional VAD Models

- **Induction**: CogVLM-17B & GPT-4
- **Deduction**: CogVLM-17B & Mistral-7B
- **Metric**: AUROC

Method	Venue	Image Only	Training	Ped2	Ave	ShT	UB
MNAD [36]	CVPR-20	✓	✓	97.0	88.5	70.5	-
rGAN [29]	ECCV-20	✓	✓	96.2	85.8	77.9	-
CDAE [9]	ECCV-20	✓	✓	96.5	86.0	73.3	-
MPN [30]	CVPR-21	✓	✓	96.9	89.5	73.8	-
NGOF [50]	CVPR-21	✗	✓	94.2	88.4	75.3	-
HF2 [25]	ICCV-21	✗	✓	**99.2**	91.1	76.2	-
BAF [14]	TPAMI-21	✗	✓	98.7	92.3	82.7	59.3
GCL [56]	CVPR-22	✗	✓	-	-	79.6	-
S3R [53]	ECCV-22	✗	✓	-	-	80.5	-
SSL [49]	ECCV-22	✗	✓	99.0	**92.2**	84.3	-
zxVAD [3]	WACV-23	✗	✓	96.9	-	71.6	-
HSC [45]	CVPR-23	✗	✓	98.1	93.7	83.4	-
FPDM [54]	ICCV-23	✓	✓	-	90.1	78.6	62.7
SLM [43]	ICCV-23	✓	✓	97.6	90.9	78.8	-
STG-NF [18]	ICCV-23	✗	✓	-	-	**85.9**	71.8
AnomalyRuler-base	-	✓	✗	96.5	82.2	84.6	69.8
AnomalyRuler	-	✓	✗	97.9	89.7	85.2	**71.9**

Two most challenging datasets

Comparison with LLM-based Approaches

- **Induction**: CogVLM-17B & GPT-4
- **Deduction**: CogVLM-17B & Mistral-7B
- **Metrics**: Accuracy/precision/recall; Doubly-right (RR/RW/WR/WW)

Method	Accuracy	Precision	Recall
Ask LLM Directly	52.1	97.1	6.2
Ask LLM with Elhafsi et al. [12]	58.4	**97.9**	15.2
Ask Video-based LLM Directly	54.7	85.4	8.5
AnomalyRuler	**81.8**	90.2	**64.3**

Method	w. Perception Errors				w/o. Perception Errors			
	RR	RW	WR	WW	RR	RW	WR	WW
Ask GPT-4 Directly	57	4	15	24	73	3	0	24
Ask GPT-4 with Elhafsi et al. [12]	60	3	15	22	76	2	0	22
Ask GPT-4V with Cao et al. [8]	74	2	7	17	81	2	0	17
AnomalyRuler	**83**	1	15	1	**99**	0	0	1

Towards Zero-Shot Anomaly Detection and Reasoning with Multimodal Large Language Models

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CVPR 2025

- One of the **first zero-shot and reasoning** methods for IAD
  - => Explain why normal/anomaly
- One of the **first instruction tuning datasets and benchmarks** for IAD reasoning
  - => Allow us to train and evaluate models for their AD reasoning capabilities

Problem Statement

Anomaly detection

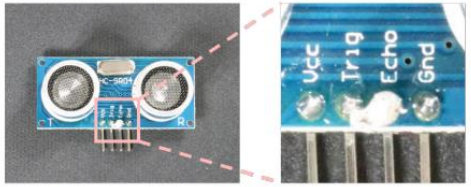
PCB Example: Excessive Solder	
	
User	Are there any anomalies visible in the image?
GPT-4o	The image shows an HC-SR04 ultrasonic sensor. There don't appear to be any visible anomalies with the sensor itself. The components and pins seem intact and properly aligned.
LLaVA-OV	The image shows an ultrasonic sensor module, specifically the HC-SR04 model. There are no visible anomalies in the image; it appears to be a standard representation of this type of sensor module.
Ours	Yes, there is a noticeable anomaly in the image: a short circuit on the PCB, indicated by a white, crusty residue near the 'Echo' pin.

Table 3. Anomaly-OV presents more accurate anomaly detection.

Basic reasoning

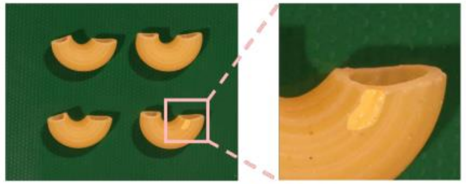
Macaroni Example: Yellowish Spot	
	
User	Do you see any anomalies in the image?
GPT-4o	The image shows four pieces of elbow macaroni on a green background. The anomaly is that the macaroni pieces are not whole; they are cut in half.
LLaVA-OV	The image shows four pieces of pasta, specifically macaroni shells, arranged on a green textured surface. The pasta appears to be uniformly colored and shaped, with no visible defects or anomalies.
Ours	Yes, there is an anomaly in the image. The bottom right pasta piece has a noticeable yellowish discoloration on its surface.

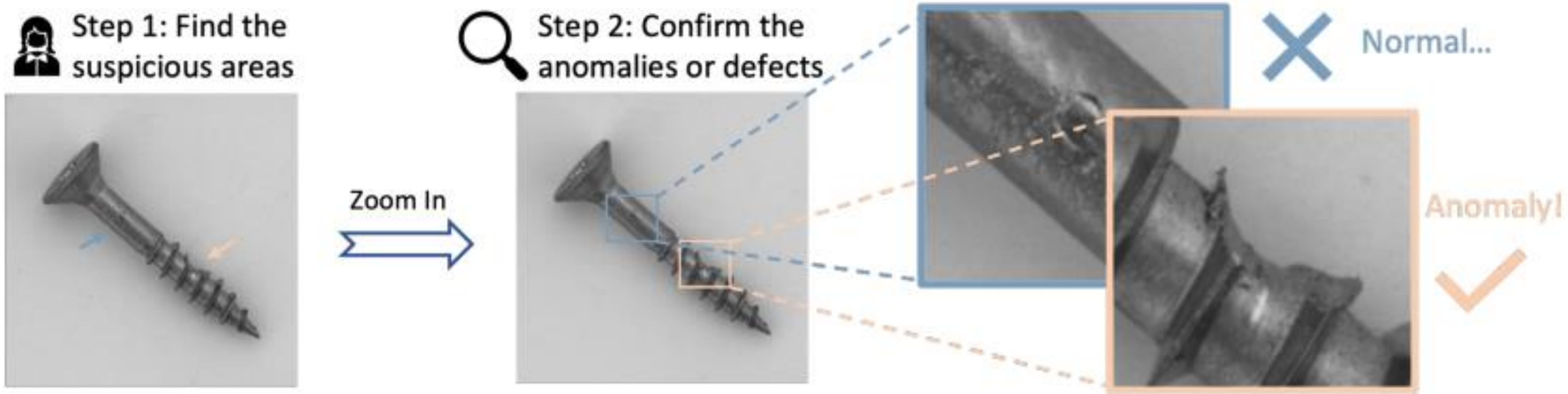
Table 5. Anomaly-OV presents more precise anomaly reasoning.

Complex reasoning

In-the-Wild Example: Graffitied Road Sign	
	
User	Describe the anomaly in the image.
Anomaly-OV	The anomaly in the image is the graffiti on the highway sign, which includes black spray paint marks and scribbles over the word 'Seattle' and other parts of the sign.
User	What is the reason for the anomaly?
Anomaly-OV	The graffiti is likely the result of vandalism, where individuals have used spray paint to deface public property for personal expression or as a form of protest.
User	How does the anomaly affect the functionality of the object?
Anomaly-OV	The graffiti affects the sign's functionality by potentially obstructing the visibility of important information, such as the word 'Seattle,' which could confuse drivers and lead to navigational errors.
User	How to avoid the anomaly in the future?
Anomaly-OV	To avoid such anomalies, regular maintenance and cleaning of signs should be implemented. Additionally, community awareness programs can help reduce vandalism by promoting respect for public property.

Method

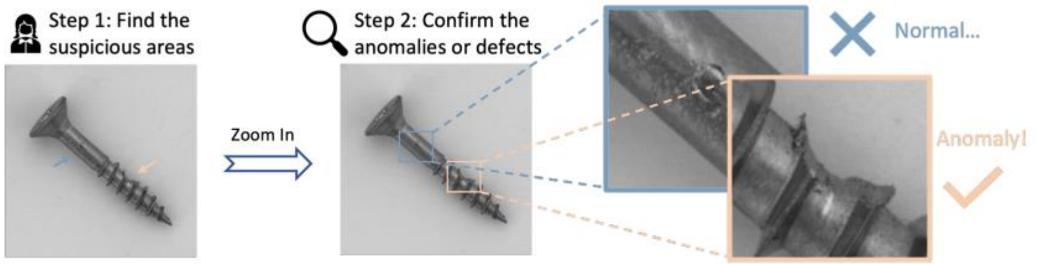
- Two-step inspection for improving detection
- Simulate human's visual anomaly inspection

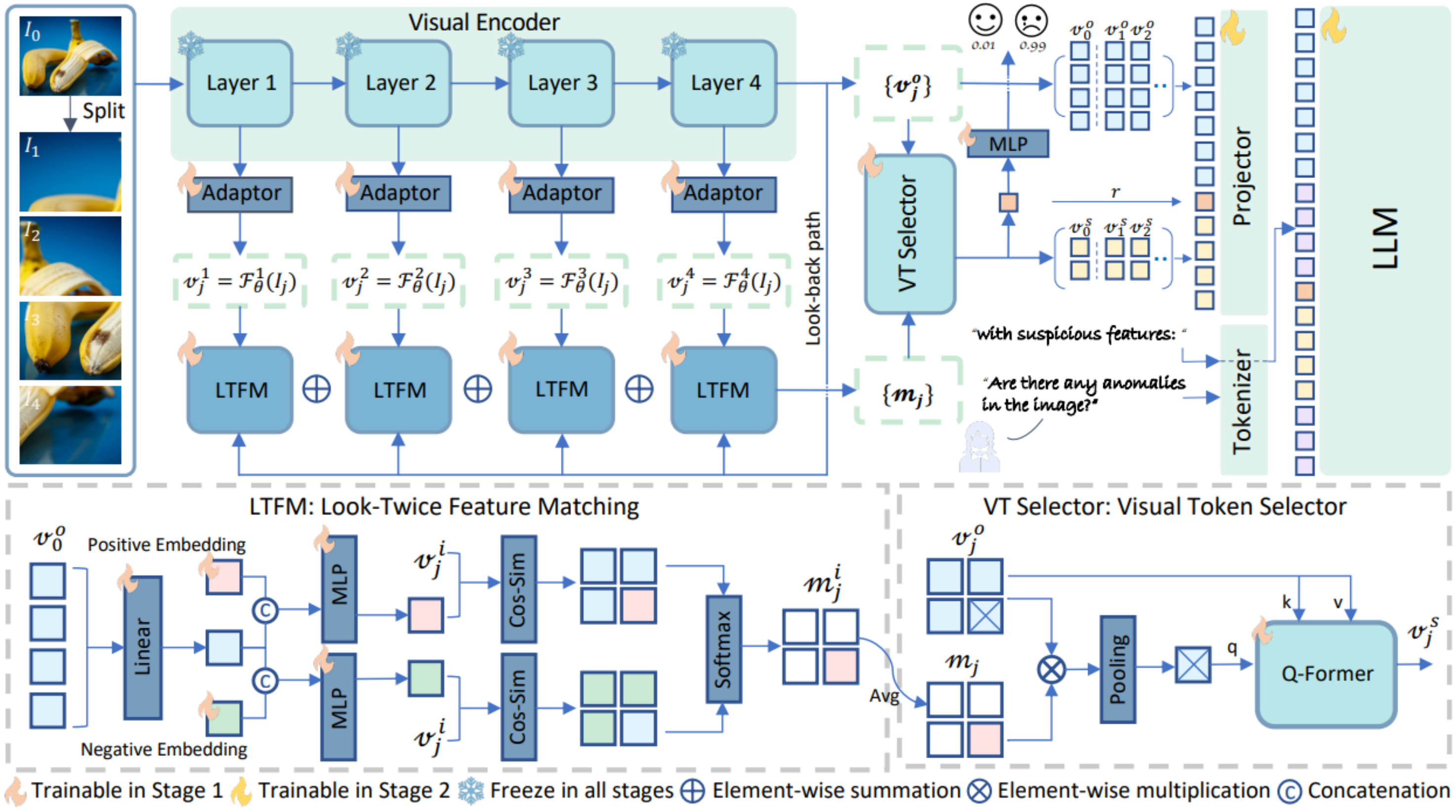


Method

- **MLLM backbone**: Visual encoder + tokenizer + projector + LLM
- **LTFM**: (Step 1) Find suspicious areas
- **VT Selector**: (Step 2) Confirm anomalies

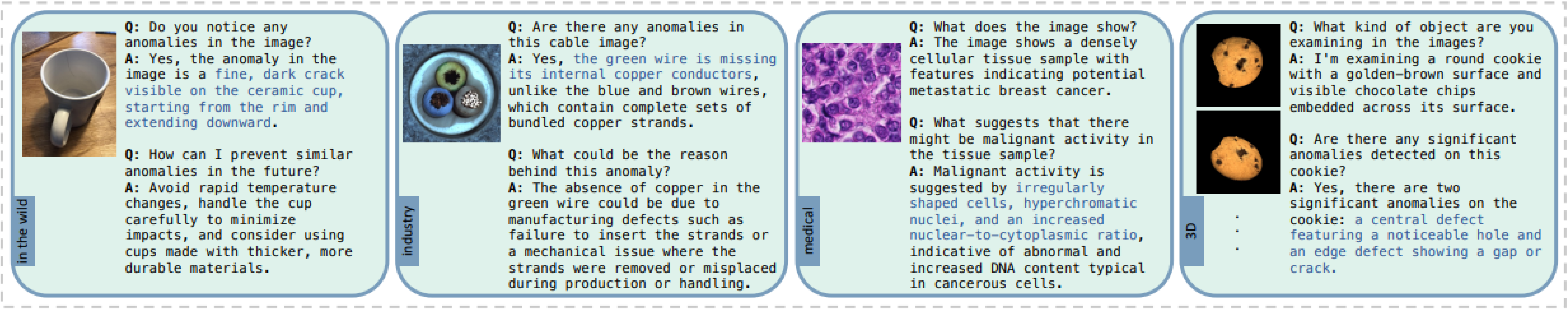
- **Training stage 1**: Train the anomaly expert (LTFM + VT Selector)
- **Training stage 2**: Visual instruction tuning (projector + LLM)





Instruction Tuning Dataset

- **Anomaly-Instruct-125k**
- Four types of images
- Visual instruction tuning for improving reasoning



WebAD-72k	MVTec AD	BMAD	MVTec-3D AD
[Collected by us via Google Image Search]	[Bergmann et al. CVPR'19]	[Bao et al. CVPR'24]	Real3D-AD
			Anomaly-ShapeNet

[Bergmann et al. 2022] [Liu et al. NeurIPS'23] [Li et al. CVPR'24]

Reasoning Benchmark

- **VisA-D&R** (761 normal + 1000 anomaly samples)
- **Detection metrics**: Accuracy/precision/recall/F1-score
- **Reasoning metrics**: ROUGE-L, Sentence-BERT, GPT-score
- **Q1 & Q2**: Basic reasoning
- **Q3 & Q4**: Complex reasoning

Detection:
Q: Are there any defects for the object in the image? Please reply with 'Yes' or 'No'.

Reasoning:
Q1: Do you observe any anomalies in the image?
Q2: Can you describe the anomalies you observed?
Q3: What is the potential cause for the anomalies?
Q4: How can such anomalies be prevented in the future?

Detection Results of Zero-Shot IAD Approaches

- MLLM backbone: LLaVA-OV [Li et al. 2024]
- Metric: AUROC

Model	Industrial Defects						Medical Anomalies			Average
	MVTec AD	VisA	AITEX	ELPV	BTAD	MPDD	BrainMRI	HeadCT	Br35H	
CLIP [73]	74.1	66.4	71.0	59.2	34.5	54.3	73.9	56.5	78.4	63.1
CoOp [108]	88.8	62.8	66.2	73.0	66.8	55.1	61.3	78.4	86.0	70.9
WinCLIP [38]	91.8	78.8	**73.0**	74.0	68.2	63.6	92.6	90.0	80.5	79.2
APRIL-GAN [11]	86.2	78.0	57.6	65.5	73.6	73.0	89.3	89.1	93.1	78.4
AnoVL [19]	92.5	79.2	72.5	70.6	80.3	68.9	88.7	81.6	88.4	80.3
AnomalyCLIP [110]	91.5	82.1	62.2	81.5	88.3	77.0	90.3	93.4	94.6	84.5
AdaCLIP [6]	89.2	85.8	64.5	79.7	88.6	76.0	**94.8**	91.4	**97.7**	85.3
Ours	**94.0**	**91.1**	72.0	**83.0**	**89.0**	**81.7**	93.9	**97.6**	95.5	**88.6**

Detection and Reasoning Results of MLLMs

- MLLM backbone: LLaVA-OV
- LLaVA-OV-0.5B*: Fine-tuned on our Anomaly-Instruct-125k

Model	Anomaly Detection				Low-level Reasoning			Complex Reasoning	
	Accuracy	Precision	Recall	F1-score	ROUGE-L	SBERT	GPT-Score	SBERT	GPT-Score
GPT-4V [71]	0.68	0.90	0.49	0.55	0.16	0.65	3.31	0.77	5.64
GPT-4o [72]	0.70	0.83	0.71	0.68	0.24	0.71	**4.84**	0.81	**6.89**
Qwen2-VL-2B [87]	0.65	0.87	0.55	0.59	0.22	0.55	1.94	0.74	4.26
Qwen2-VL-7B [87]	0.76	<u>0.91</u>	0.69	0.75	0.25	0.61	3.09	0.68	4.62
InternVL-2-8B [13]	0.74	0.78	0.81	0.76	0.23	0.73	3.69	0.80	5.08
InternVL-2-26B [13]	0.73	0.86	0.66	0.68	0.21	**0.74**	4.13	0.80	5.49
IXC-2.5-7B [101]	0.72	0.88	0.63	0.67	0.21	0.58	2.45	0.77	5.14
LLaVA-OV-0.5B [44]	0.54	0.70	0.19	0.28	0.20	0.63	2.54	0.81	4.34
LLaVA-OV-7B [44]	0.71	**0.95**	0.56	0.63	0.24	0.66	3.57	0.79	5.44
LLaVA-OV-0.5B*	0.71	0.77	<u>0.84</u>	0.76	0.31	0.70	3.69	0.82	5.31
Anomaly-OV-0.5B	**0.79**	0.86	0.83	<u>0.82</u>	<u>0.33</u>	0.72	3.87	<u>0.83</u>	5.67
Anomaly-OV-7B	**0.79**	0.83	**0.86**	**0.83**	**0.34**	<u>0.73</u>	<u>4.26</u>	**0.84**	<u>6.34</u>

Summary

ECCV 2024

Video Anomaly Detection (VAD)

CVPR 2025

Image Anomaly Detection (IAD)

	Conventional		**MLLMs**
How to learn	Full-shot training	→	Few-shot / Zero-shot
What to output	Detection only (anomaly scores)	→	Detection + Reasoning

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- New metrics
- New benchmarks