

Towards Generic Anomaly Detection and Understanding: Large-scale Visual-linguistic Model (GPT-4V) Takes the Lead

Yunkang Cao^{1*}, Xiaohao Xu^{2*}, Chen Sun^{3*}, Xiaonan Huang² and Weiming Shen¹

¹Huazhong University of Science and Technology ²University of Michigan, Ann Arbor

³University of Toronto

Abstract

Anomaly detection is a crucial task across different domains and data types. However, existing anomaly detection models are often designed for specific domains and modalities. This study explores the use of GPT-4V(ision), a powerful visual-linguistic model, to address anomaly detection tasks in a generic manner. We investigate the application of GPT-4V in multi-modality, multi-domain anomaly detection tasks, including image, video, point cloud, and time series data, across multiple application areas, such as industrial, medical, logical, video, 3D anomaly detection, and localization tasks. To enhance GPT-4V's performance, we incorporate different kinds of additional cues such as class information, human expertise, and reference images as prompts. Based on our experiments, GPT-4V proves to be highly effective in detecting and explaining global and fine-grained semantic patterns in zero/one-shot anomaly detection. This enables accurate differentiation between normal and abnormal instances. Although we conducted extensive evaluations in this study, there is still room for future evaluation to further exploit GPT-4V's generic anomaly detection capacity from different aspects. These include exploring quantitative metrics, expanding evaluation benchmarks, incorporating multi-round interactions, and incorporating human feedback loops. Nevertheless, GPT-4V exhibits promising performance in generic anomaly detection and understanding, thus opening up a new avenue for anomaly detection.

All evaluation samples, including image and text prompts, will be available at <https://github.com/caoyunkang/GPT4V-for-Generic-Anomaly-Detection>.

Contents

1	Introduction	5
1.1	Motivation and Overview	5
1.2	Our Approach: Prompting GPT-4V for Anomaly Detection	5
1.2.1	Prompt Designs	5
1.2.2	Evaluation Scope: Modalities and Domains	6
1.3	Limitations in Anomaly Detection Evaluation Based on GPT-4V	6
2	Observations of GPT-4V on Multi-modal Multi-domain Anomaly Detection	7
2.1	GPT-4V can address multi-modality and multi-field anomaly detection tasks in zero/one-shot regime:	7
2.2	GPT-4V can understand both global and fine-grained semantics for anomaly detection:	7
2.3	GPT-4V can automatically reason for anomaly detection:	8
2.4	GPT-4V can be enhanced with increasing prompts:	8

* Authors contribute equally. Email: cyk_hust@hust.edu.cn, xiaohaox@umich.edu, chrn.sun@mail.utoronto.ca, xiaonanh@umich.edu, wshen@ieee.org

2.5 GPT-4V can be constrained in real-world application but still promising:	8
3 Industrial Image Anomaly Detection	8
3.1 Task Introduction	8
3.2 Testing philosophy	8
3.3 Case Demonstration	10
4 Industrial Image Anomaly Localization	10
4.1 Task Introduction	10
4.2 Testing philosophy	10
4.3 Case Demonstration	10
5 Point Cloud Anomaly Detection	10
5.1 Task Introduction	10
5.2 Testing philosophy	11
5.3 Case Demonstration	11
6 Logical Anomaly Detection	11
6.1 Task Introduction	11
6.2 Testing philosophy	11
6.3 Case Demonstration	12
7 Medical Image Anomaly Detection	12
7.1 Task Introduction	12
7.2 Testing philosophy	12
7.3 Case Demonstration	13
8 Medical Image Anomaly Localization	13
8.1 Task Introduction	13
8.2 Testing philosophy	13
8.3 Case Demonstration	13
9 Pedestrian Anomaly Detection	14
9.1 Task Introduction	14
9.2 Testing philosophy	14
9.3 Case Demonstration	14
10 Traffic Anomaly Detection	14
10.1 Task Introduction	14
10.2 Testing philosophy	14
10.3 Case Demonstration	15
11 Time Series Anomaly Detection	15

11.1 Task Introduction	15
11.2 Testing philosophy	15
11.3 Case Demonstration	15
12 Prospect	15
13 Conclusion	16

List of Figures

1	The Diagram of Evaluation GPT-4V on Multi-modality/fields Anomaly Detection.	6
2	Industrial Image Anomaly Detection: Case 1	9
3	Industrial Image Anomaly Detection: Case 1	17
4	Industrial Image Anomaly Detection: Case 2	18
5	Industrial Image Anomaly Detection: Case 2	19
6	Industrial Image Anomaly Detection: Case 3	20
7	Industrial Image Anomaly Detection: Case 3	21
8	Industrial Image Anomaly Localization: Case 1	22
9	Industrial Image Anomaly Localization: Case 2	23
10	Industrial Image Anomaly Localization: Case 3	24
11	Point Cloud Anomaly Detection: Case 1	25
12	Point Cloud Anomaly Detection: Case 1	26
13	Point Cloud Anomaly Detection: Case 2	27
14	Point Cloud Anomaly Detection: Case 2	28
15	Point Cloud Anomaly Detection: Case 3	29
16	Point Cloud Anomaly Detection: Case 3	30
17	Logical Anomaly Detection: Case 1	31
18	Logical Anomaly Detection: Case 2	32
19	Logical Anomaly Detection: Case 3	33
20	Logical Anomaly Detection: Case 4	34
21	Medical Anomaly Detection: Case 1	35
22	Medical Anomaly Detection: Case 1	36
23	Medical Anomaly Detection: Case 2	37
24	Medical Anomaly Detection: Case 2	38
25	Medical Anomaly Detection: Case 3	39
26	Medical Anomaly Detection: Case 3	40
27	Medical Anomaly Detection: Case 4	41
28	Medical Anomaly Detection: Case 4	42
29	Medical Anomaly Localization: Case 1	43
30	Medical Anomaly Localization: Case 2	44
31	Medical Anomaly Localization: Case 3	45
32	Medical Anomaly Localization: Case 4	46
33	Pedestrian Anomaly Detection	47
34	Traffic Anomaly Detection: Case 1	48
35	Traffic Anomaly Detection: Case 2	49
36	Time Series Anomaly Detection: Case 1	50
37	Time Series Anomaly Detection: Case 2	51

1 Introduction

1.1 Motivation and Overview

Anomaly detection [20, 19, 72, 10, 78] involves identifying data patterns or data points that significantly deviate from normality. These anomalies or outliers are rare, unusual, or inconsistent data points that deviate from the majority of the data. The primary objective of anomaly detection is to automatically detect and pinpoint these irregularities, which may signify errors, fraud, unusual events, or other noteworthy phenomena, facilitating further investigation or necessary action. Anomaly detection techniques have been widely employed in diverse domains, such as industrial inspection [29, 98], medical diagnosis [107], video surveillance [84], fraud detection [30] and many other areas where identifying unusual instances is crucial.

Despite the existence of numerous techniques [14, 3, 69, 41, 38, 79, 110, 16, 103] for anomaly detection, many existing approaches predominantly rely on methods that describe the normal data distribution. They often overlook high-level perception and primarily treat it as a low-level task. However, practical applications of anomaly detection frequently necessitate a more comprehensive, high-level understanding of the data. Achieving this understanding entails at least three crucial steps:

1. **Understanding the Data Types and Categories:** The first step involves a thorough comprehension of the data types and categories present in the dataset. Data can take various forms, including images, videos, point clouds, time-series data, etc. Each data type may require specific methods and considerations for anomaly detection. Furthermore, different categories may have distinct definitions of normal states.
2. **Determining Standards for Normal States:** After obtaining the data types and categories, it would be feasible to further reason the standards for normal states, which requires a high-level understanding of the data.
3. **Evaluating Data Conformance:** The final step is to assess whether the provided data conforms to the established standards for normality. Any deviation from these standards can be categorized as an anomaly.

Recent advancements in large multimodal models (LMMs) [25, 4, 36, 113, 58, 27, 52] have shown robust reasoning capacity [55, 57] and created new opportunities for improving anomaly detection. LMMs are typically trained on extensive multimodal datasets [80], enabling them to effectively analyze various data types, including natural language and visual information. They hold the potential to address the challenges associated with high-level anomaly detection [37, 17, 22, 112].

Moreover, OpenAI recently introduced GPT-4V(ision) [101], a state-of-the-art LMM that has exhibited remarkable performance across various practical applications. However, it remains uncertain whether GPT-4V can also exhibit robust capabilities for anomaly detection. The objective of this study is to bridge this knowledge gap by assessing the anomaly detection capabilities of GPT-4V.

1.2 Our Approach: Prompting GPT-4V for Anomaly Detection

1.2.1 Prompt Designs

The design of prompts plays a crucial role in effectively directing GPT-4V's attention toward the specific aspects of the anomaly detection task. In this study, we primarily consider four types of prompts:

1. **Task Information Prompt:** To prompt GPT-4V effectively for anomaly detection, it is essential to provide clear task information. This study formulates the prompt as follows: "Please determine whether the image contains anomalies or outlier points."
2. **Class Information Prompt:** The understanding of data types and categories is critical. In cases where GPT-4V may struggle to recognize the data class, explicit class information may be provided. For instance, "Please determine whether the image, which is related to the {CLS}, contains anomalies or defects."

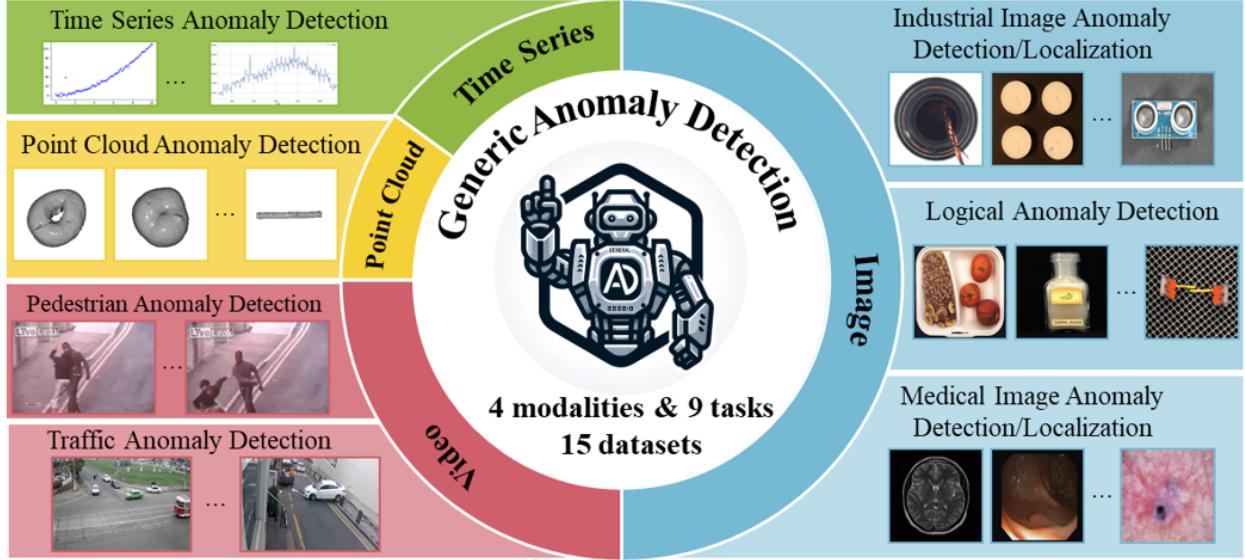


Figure 1 | Comprehensive Evaluation of GPT-4V for Multi-modality Multi-task Anomaly Detection In this study, we conduct a thorough evaluation of GPT-4V in the context of multi-modality anomaly detection. We consider four modalities: image, video, point cloud, and time series, and explore nine specific tasks, including industrial image anomaly detection/localization, point cloud anomaly detection, medical image anomaly detection/localization, logical anomaly detection, pedestrian anomaly detection, traffic anomaly detection, and time series anomaly detection. Our evaluation encompasses a diverse range of 15 datasets.

3. **Normal Standard Prompt:** GPT-4V may encounter difficulties in answering questions related to determining normal standards, and sometimes the standards even can not be examined without human expertise. Hence, this study also explicitly provides the normal standards. For example, normal standards for the breakfast box in MVTec-LOCO [7] could be expressed as follows: "1. It should contain two oranges, one peach, and some cereal, nuts, and banana slices; 2. The fruit should be on the left side of the lunchbox, the cereal on the upper right, and the nuts and banana slices on the lower right of the lunchbox."
4. **Reference Image Prompt:** To ensure better alignment between normal standards and images, a normal reference image is provided alongside language prompts. For example, "The first image is normal. Please determine whether the second image contains anomalies or defects."

The study aims to explore how the use of these prompts, either individually or in different combinations depending on certain cases, impacts GPT-4V's capacity for anomaly detection.

1.2.2 Evaluation Scope: Modalities and Domains

Extensive evaluations are conducted in this study to assess the capabilities of GPT-4V in anomaly detection, as Fig. 1 shows. From the perspective of modalities, we evaluate image (Section 3, 4, 6, 7, 8), point cloud (Section 5), video (Section 9, 10), and time series (Section 11). From the perspective of fields, industrial inspection (Section 3, 4, 6, 5), medical diagnosis (Section 7, 8), and video surveillance (Section 9, 10) are evaluated. To the best of our knowledge, this is the first study to investigate such a wide range of modalities and fields for anomaly detection.

1.3 Limitations in Anomaly Detection Evaluation Based on GPT-4V

The analysis of this study is subject to certain limitations:

1. **Predominance of Qualitative Results:** The analysis primarily relies on qualitative assessment,

lacking quantitative metrics that could offer a more objective evaluation of the model's performance in anomaly detection. Incorporating quantitative measures would provide a more robust basis for assessment.

2. **Scope of Evaluated Cases:** The evaluation is confined to a limited scope of cases or scenarios. This narrow focus may not fully capture the diverse challenges encountered in real-world anomaly detection tasks. Expanding the range of evaluated cases would yield a more comprehensive understanding of the model's capabilities.
3. **Single Interaction Evaluation:** The study mainly concentrates on a single-round conversation. In contrast, multi-round conversations, as observed in the in-context learning capacity of GPT-4V [101], can stimulate deeper interaction. The single-round conversation approach restricts the depth of interaction and may constrain the model's comprehension and its effectiveness in responding to anomaly detection tasks. Exploring multi-round interactions could reveal a more nuanced perspective of the model's performance.

2 Observations of GPT-4V on Multi-modal Multi-domain Anomaly Detection

Following a thorough evaluation of GPT-4V's performance across various multi-modality and multi-field anomaly detection tasks, it becomes apparent that GPT-4V possesses robust anomaly detection capabilities. More precisely, GPT-4V consistently excels in addressing the three previously mentioned challenges: comprehending image context, discerning normal standards, and effectively comparing the provided image against these standards. In addition to these fundamental findings, our assessments have yielded valuable insights.

2.1 GPT-4V can address multi-modality and multi-field anomaly detection tasks in zero/one-shot regime:

Anomaly detection for multi-modality: GPT-4V's ability to handle diverse data modalities is demonstrated by its consistent performance across various domains. For instance, it exhibits proficiency in identifying anomalies in images, point clouds, X-rays, etc., underscoring its adaptability to multi-modal tasks. This versatility allows it to transcend the limitations of single-modal anomaly detectors.

Anomaly detection for multi-field: GPT-4V's performance across multiple fields, including industrial, medical, pedestrian, traffic, and time series anomaly detection, showcases its ability to seamlessly adapt to the distinct characteristics of each domain. Its consistent results affirm its broad applicability and versatility, making it a valuable tool for anomaly detection in a variety of real-world contexts.

Anomaly detection in zero/one-shot regime: GPT-4V's evaluation in both zero-shot and one-shot settings highlights its adaptability to different inference scenarios. In the absence of reference images, the model effectively relies on language prompts to detect anomalies. However, when provided with normal reference images, its anomaly detection accuracy is further enhanced. This flexibility enables GPT-4V to cater to a wide range of anomaly detection applications, whether with or without prior knowledge.

2.2 GPT-4V can understand both global and fine-grained semantics for anomaly detection:

GPT-4V's understanding of global semantics: GPT-4V's capacity to comprehend global semantics is demonstrated in its ability to recognize overarching abnormal patterns or behaviors. For example, in traffic anomaly detection, it can discern the distinction between typical traffic flow and irregular events, providing a holistic interpretation of the data. This global understanding makes it well-suited for identifying anomalies that deviate from expected norms in a broader context.

GPT-4V's understanding of fine-grained semantics: GPT-4V's fine-grained anomaly detection capabilities shine in cases where it not only detects anomalies but also precisely localizes them within complex data. For instance, in industrial image anomaly detection, it can pinpoint intricate details like slightly tilted wicks on candles or minor scratches or residues around the top rim of the bottle. This fine-grained understanding enhances its ability to detect subtle anomalies within complex data, contributing to its overall effectiveness.

2.3 GPT-4V can automatically reason for anomaly detection:

The model's strength in automatically reasoning the given complex normal standards and generating explanations for detected anomalies is a valuable feature. In logical anomaly detection, for example, GPT-4V excels at dissecting complex rules and providing detailed analyses of why an image deviates from the expected standards. This inherent reasoning ability adds a layer of interpretability to its anomaly detection results, making it a valuable tool for understanding and addressing irregularities in various domains.

2.4 GPT-4V can be enhanced with increasing prompts:

The results of the evaluation highlight the positive impact of additional prompts on GPT-4V's anomaly detection performance. The model's response to class information, human expertise, and reference images suggests that providing it with more context and information significantly improves its ability to detect anomalies accurately. This feature allows users to fine-tune and enhance the model's performance by providing relevant and supplementary information.

2.5 GPT-4V can be constrained in real-world application but still promising:

From the cases we test, we find there are still several gaps for GPT4V models to be applied in real world anomaly detection. For example, GPT-4V may face challenges in handling highly complex scenarios for industrial application. Ethical constraints in the medical field also make it conservative and hesitate to give confident answer. But we believe it remains promising in a wide range of anomaly detection tasks. To address these challenges effectively, further enhancements, specialized fine-tuning, or complementary techniques may be required. GPT-4V's potential for anomaly detection is evident, and ongoing research may continue to unlock its capabilities in even more complex scenarios.

3 Industrial Image Anomaly Detection

3.1 Task Introduction

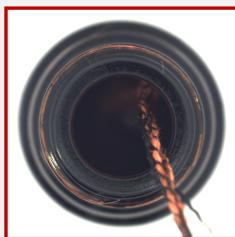
Industrial image anomaly detection is a critical component of manufacturing processes aimed at upholding product quality [6, 98, 14]. Following the establishment of the MVTec AD dataset [6], various methods [15, 45, 22, 17, 15, 46, 92] have thrived in this field. These methods focus on determining whether testing images contain anomalies, typically represented as local structural variants. Early methods [91, 95, 102, 13, 54, 94] concentrated on developing specific models for given categories, while recent approaches [45, 22, 17, 112] target a more general but challenging solution, i.e., developing a unified model for arbitrary product categories, which usually performs in few-shot [99, 40] or even zero-shot [45, 17, 22] regime. As highlighted in [101], GPT-4V, equipped with extensive world knowledge, presents a promising solution for arbitrary category inspection.

3.2 Testing philosophy

Different prompts [101, 56] could lead to different responses from GPT-4V. We aim to investigate the influence of different information on prompting GPT-4V for industrial anomaly detection. Following the previously discussed problems, this study further develops three prompts, a) class information: the names of the desired inspecting products, such as "bottle" and "candle", b) human expertise: the normal appearance and potential abnormal states and express them in languages, e.g., "Normally, the image given should show a clean and well-structured printed circuit board (PCB) with clear traces, soldered components, and distinct labels. It may have defects such as bent pins, cold solder joints, missing components, or smudged labels", c) reference image: normal reference image to provide GPT-4V a better understanding of normality. We propose to evaluate GPT-4V in either a zero-shot setting, with only language prompts, or a one-shot setting, with one reference image provided along with the language prompts. For each setting, we test three different variants: a) a naive prompt like "Please determine whether the image contains anomalies or defects," b) with class information, and c) with human expertise.

Industrial Image Anomaly Detection: Case1

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The image appears to show a circular object, possibly the top of a bottle or container, with a rope or cord passing through it. Upon examination: 1. There seems to be some debris or particles on the rim of the circular object. 2. The rim has visible scratches or scuffs. 3. There are some irregularities or potential defects on the cord, with areas appearing frayed or worn out.

Zero-shot (with class information)

Language Prompt

Please determine whether the image given about the **bottle** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

1. There's a strand or cord-like material partially inside and outside the bottle. This might not be a defect if it's meant to be there, but in the context of a pure bottle inspection, it could be seen as an anomaly. 2. There seem to be minor scratches or residues around the top rim of the bottle. This could be considered a defect depending on the intended quality and usage of the bottle. 3. The inner rim of the bottle displays some unevenness or potential residue, which may or may not be a defect based on the manufacturing standards.

Zero-shot (with human expertise)

Prompt

Please determine whether the image given about the **bottle** contains anomalies or defects. If yes, give a specific reason. **Normally, the image given should depict clear and identifiable bottles. It may have defects such as broken parts, contaminations.**

GPT-4V

1. There appears to be some string or thread-like material partially immersed inside the bottle. This could be a contamination or a foreign object that isn't typically expected in a clear bottle. 2. The rim of the bottle shows some irregularities or potential residues. Based on these observations, it appears that the bottle may have contaminants or anomalies.

Figure 2 | Industrial Image Anomaly Detection: Case 1, zero-shot, the Bottle category of MVTec AD [6]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

3.3 Case Demonstration

Fig. 2, 3, 4, 5, 6, 7 qualitatively demonstrate the effectiveness of GPT-4V for industrial image anomaly detection. Even with a simple language prompt, GPT-4V effectively identifies anomalies in examined bottle and candle images, showcasing its capacity and versatility. Moreover, GPT-4V excels not only in detecting desired anomalies but also in identifying fine-grained structural anomalies. As evident in Fig. 4, GPT-4V noticed a slightly tilted wick on the bottom left candle, demonstrating its nuanced understanding. In complex cases like Fig. 6, GPT-4V recognizes the PCB in images and provides in-depth reasoning about anomalies, such as examining the proper seating of the ultrasonic sensor. However, GPT-4V overlooks the bent pin, resulting in an incorrect result. Nevertheless, GPT-4V showcases a strong grasp of image context and category-specific anomaly understanding.

4 Industrial Image Anomaly Localization

4.1 Task Introduction

Industrial image anomaly localization entails a more intricate process than mere image anomaly detection [76, 93, 12, 13, 65]. It goes beyond recognizing the abnormality within an image and extends to precisely identifying the location of these anomalies. While GPT-4V has exhibited localization capabilities in various domains [101, 97, 100], its potential for image anomaly localization warrants further exploration.

Regrettably, GPT-4V does not currently have the capability to directly produce prediction masks. Some methods have attempted to leverage GPT-4V by prompting it to provide bounding boxes [101, 97]. However, this approach appears to be imprecise and poses challenges for GPT-4V. In contrast, the approach presented by SoM [100] involves utilizing SAM [50] to generate visual prompts [81, 50], which are presented in numbered markers. This visual prompting technique shifts the localization task from a pixel-level mask prediction task to a mask-level classification task, effectively reducing the associated complexities and increasing localization precision.

4.2 Testing philosophy

To harness the fine-grained localization capability of GPT-4V, we adopt the approach outlined in SoM [100]. This involves generating a set of image-mask pairs for prompting GPT-4V. In addition to the image-mask pairs, we employ a straightforward language prompt that instructs the model, as follows: "The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the image contains anomalies or defects. If yes, give a specific reason".

4.3 Case Demonstration

Fig. 8, 9, and 10 provide a visual representation of GPT-4V's performance in industrial anomaly localization. These illustrations clearly illustrate GPT-4V's ability to accurately identify the second mask in Fig. 8 as a twisted wire and the second mask in Fig. 9 as holes. These results serve as compelling evidence of GPT-4V's proficiency in localizing anomalies when guided by visual prompts.

It is important to acknowledge that GPT-4V does exhibit certain limitations when confronted with more complex scenarios, as evidenced in Fig. 10. However, the combination of visual prompting techniques and GPT-4V remains a promising approach for industrial anomaly localization.

5 Point Cloud Anomaly Detection

5.1 Task Introduction

Geometrical information, as discussed in references such as PAD [111], Real3D [59], and MVTec-3D [8], holds a crucial role in fields like industrial anomaly detection, especially when dealing with categories lacking textual information. Recently, MVTec 3D [8] and Real3D [59] have recognized the growing need for such information and have introduced a point cloud anomaly detection task. This task focuses on the identification of anomalies

within the provided point clouds [32].

It is important to note that the success achieved in industrial image anomaly detection is not fully mirrored in point cloud anomaly detection. This disparity is primarily attributed to the reliance of industrial image anomaly detection on robust pre-trained networks [12, 75, 39]. Conversely, due to the scarcity of extensive point cloud data, the capabilities of pre-trained networks for point clouds currently fall short, leading to suboptimal performance for some methods [96, 21, 9, 77].

In contrast, CPMF [16] proposes a novel approach by transforming point clouds into depth images, thereby opening up the possibility of leveraging image-based foundation models for point cloud anomaly detection. This innovative method has shown the potential to deliver significantly improved results in point cloud anomaly detection.

5.2 Testing philosophy

To employ GPT-4V in the context of point cloud anomaly detection, we adopt the methodology presented in CPMF [16] to transform point clouds into multi-view depth images. In our evaluation, we adhere to the principles commonly used in industrial image anomaly detection, specifically the zero/one-shot approach, with the inclusion of three distinct variations of language prompts.

5.3 Case Demonstration

Fig. 11, 12, 13, 14, 15, 16 provide a visual representation of the performance of GPT-4V in point cloud anomaly detection. These illustrations serve to qualitatively illustrate the proficiency of GPT-4V in comprehending multi-modality data.

Specifically, GPT-4V demonstrates its capability to accurately identify the presence of a small protrusion or bump on the top left part of the torus in the bagel (Fig. 11). Moreover, the introduction of additional information, such as class information and human expertise, enhances the performance of GPT-4V in point cloud anomaly detection, allowing it to effectively detect anomalies in the rope (Fig. 15 and 16).

However, it is noteworthy that GPT-4V may occasionally misidentify artificially introduced elements during the rendering process as anomalies, as observed in Fig. 14. It is possible that improvements in rendering quality could further enhance the capacity of GPT-4V in this context.

6 Logical Anomaly Detection

6.1 Task Introduction

In addition to structural anomalies, there exists another type of anomaly, named logical anomalies [7]. Logical anomalies generally refer to incorrect combinations of components, commonly encountered in the context of anomaly detection in assemblies. For instance, a screw bag should contain matched screws, nuts, and washers. This necessitates that the model is capable of understanding fine-grained information in images and determining attributes of the components within the image, such as component type, length, color, quantity, and so forth. This places higher demands on the model. Existing logical anomaly detection methods [63, 103, 5, 106] typically relied on solely visual context and have achieved promising detection performance. However, these approaches do not genuinely comprehend the content of images; instead, they rely on global-local correspondences [98] for logical anomaly detection. This does not effectively address logical anomaly detection. In contrast, GPT-4V possesses robust image understanding capabilities, allowing for a better comprehension of image content. By providing predefined normal rules manually, GPT-4V might be capable of determining whether an image adheres to normal rules, thereby enabling a more rational approach to logical anomaly detection.

6.2 Testing philosophy

To ensure an effective assessment of testing images, it is crucial to provide clear guidelines defining the expected normal state for GPT-4V. This enables GPT-4V to evaluate the conformity of testing images with

the established standards, relying on an analysis of image content in relation to these norms. Consequently, our approach involves presenting GPT-4V with both testing images and descriptive language articulating the expected normal standards. However, it is worth noting that GPT-4V might encounter difficulties in comprehending the nuances of normal standards when presented with language alone. To enhance its understanding and alignment of normal standards with the context of normal images, we propose the inclusion of a reference image illustrating the desired normal state. Therefore, our experimental design encompasses both zero-shot and one-shot settings to assess the effectiveness of this approach.

6.3 Case Demonstration

The evaluation results, as depicted in Fig. 17, 18, 19, 20, unequivocally highlight the robust image comprehension and logical reasoning capabilities of GPT-4V. For instance, in Fig. 17, GPT-4V demonstrates its proficiency in interpreting intricate standards, encompassing criteria such as the presence of "1. It should contain two oranges, one peach, and some cereal, nuts, and banana slices; 2. The fruit should be on the left side of the lunch box, the cereal on the upper right, and the nuts and banana slices on the lower right of the lunch box". GPT-4V adeptly breaks down this complex task into subcomponents, identifying and localizing the various items before calculating their quantities and positions. Ultimately, GPT-4V accurately concludes that the provided breakfast box does not adhere to the stipulated standards.

Moreover, visual references play a pivotal role in enhancing GPT-4V's performance. In Fig. 18, without the aid of a visual reference, GPT-4V erroneously classifies the juice bottle as a normal one. However, when presented with a referenced image, GPT-4V effectively comprehends the rule "2. To prevent bottle explosions, ensure the juice is filled to about 3cm below the bottle's opening" and delivers a correct analysis.

Nonetheless, GPT-4V may encounter challenges in scenarios where its ability to contextualize images is constrained. Notably, GPT-4V fails to detect a broken cable in Fig. 19 and inaccurately quantifies washers in Fig. 20. The limitations of GPT-4V, particularly in matters of fine-grained details like counting, have been addressed in prior research [101]. Furthermore, it is worth noting that multi-round conversations and specific language prompts can significantly impact GPT-4V's performance in such cases.

7 Medical Image Anomaly Detection

7.1 Task Introduction

Anomaly detection, also known as outlier detection, is a pivotal task in the domain of medical imaging, aimed at identifying abnormal patterns that do not conform to expected behavior[31]. These abnormalities or anomalies could be indicative of a wide range of medical conditions or diseases[citation]. The primary goal of anomaly detection is to accurately discern these irregularities from a plethora of medical imaging data, thereby aiding in early diagnosis and effective treatment planning. Current medical anomaly detection methods can be categorized into reconstruction-based methods [23] [35] [90], GAN-based [61], self-supervised methods [82] [88] [87] and pre-train methods [75] [28] [60] [62]. Although these methods have achieved great improvements, a unified anomaly detection model across different diseases and modalities still remains an unsolved challenge. As highlighted in [71] and [97], GPT-4V, equipped with numerous multi-modal knowledge, shows promising future in enhancing the performance of anomaly detection tasks in various medical imaging modalities.

7.2 Testing philosophy

We aim to investigate the generalization abilities of GPT-4V on medical anomaly detection. Thus medical images on across different diseases and modalities are used, including Head MRI, Head CT, Retinal OCT, Chest X-ray and so on. For the text prompt, we also take the previous multi-step prompt to test its zero-shot and one-shot abilities. There are generally three types of prompts, a)general medical information, the disease and modalities of the medical images, such as "Chest X-ray Image" or "Head CT Image" b)human expertise, based on the general medical information, we further give the possible disease name in the medical image, e.g."The image should be classified as normal or hemorrhage", c) reference image: normal reference image to provide GPT-4V a better understanding of nomrality.

We propose to evaluate GPT-4V in either a zero-shot setting, with only language prompts, or a one-shot setting, with one reference image provided along with the language prompts. For each setting, we test three different variants: a) a naive prompt like "Please determine whether the image contains anomalies" b) general medical information, and c) with human expertise.

7.3 Case Demonstration

Fig. 21, 23, 25 and 27 show the GPT-4V's zero-shot inference ability. GPT-4V is capable of automatically recognizing medical image modalities and anatomical structures, even without general medical information prompts. The superior image caption ability enables GPT-4V to describe the spatial and textural anomalies in the image. However, due to ethical restrictions, the GPT-4V model tends to give conservative answers when lack of sufficient information. The introduction of both general medical information and human expertise successfully leads GPT-4V to generate more concrete and accurate answers, as shown in Fig 21, 23 and 25. However, GPT-4V fails to recognize anomalies in Fig 27, even with enough information provided. The abnormal area is not obvious in the image, so it turns out that it has high requirements for the medical image quality. When a visual reference is added, the GPT-4V's image caption ability successfully describe the difference between normal and abnormal images, which is shown in Fig 22, 24 26 and 28.

8 Medical Image Anomaly Localization

8.1 Task Introduction

Following the detection of medical anomaly, the subsequent critical task is anomaly localization, which entails pinpointing the exact spatial location of the identified anomaly within the medical image [88] [104]. Accurate localization is imperative for clinicians to understand the extent and nature of the pathology, which in turn informs the course of clinical intervention. However, the real-world clinical scenario, such as tumor anomaly localization, is more complex, where either normal or abmoral cases have multiple types of tumors. Establishing a direct relationship between image pixels and excessive semantics (types of tumors) is difficult for real world medical image anomaly localization. Several methods, including self-supervised based method [88] and cluster-based method [104] have been proposed to deal with the medical image anomaly localization task. Inspired by [100], we would like to examine the localization ability of GPT-4V model, under the visual prompts.

8.2 Testing philosophy

To test the GPT-4V's ability on medical image localization, we utilize several diseases categories and modalities, including abdominal CT image, endoscopy image, head MRI image and skin lesion image. Both diseased area and manually synthetic abnormal are taken into consideration to test its robustness. The visual prompts proposed by [100] are also used to harness the fine-grained localization abilities of GPT-4V, including a set of image-mask pairs and corresponding index numbers to each mask. Thus, the input images are the raw images with the augmented one with masks and numbers. We also adopt a straightforward text prompt to introduce the relationship between the two input images, as follows: "The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the image contains anomalies or defects. If yes, give a specific reason"

8.3 Case Demonstration

The qualitative results are shown in Fig 29 30 31 and 32. Under the instruction of visual prompts in the images, the GPT-4V tends to learn and caption the areas around the marks. For easily recognized and located cases, such as Fig 30 31 and 32, GPT-4V can clearly tell the difference between the anomaly areas and backgrounds. But GPT-4V fails in Fig 29, a synthetic case where the region-of-interest shares a similar texture and shape with the background. This indicates that this model still needs to improve its detection and localization abilities under adversarial attack and complex backgrounds.

9 Pedestrian Anomaly Detection

9.1 Task Introduction

Pedestrian anomaly detection, a subset of video anomaly detection, is dedicated to recognizing irregular activities within pedestrian interactions captured in video streams. Traditional methodologies, as referenced by various studies [1, 69, 33, 109, 64, 86, 105, 44], primarily rely on rule-based approaches and manually engineered features. In recent times, there has been a noticeable shift towards the adoption of deep learning techniques [38, 24, 66, 74, 73, 53, 42, 43, 41] for pedestrian anomaly detection. The complexity of pedestrian anomaly detection arises from the need to accurately identify abnormal behaviors within the context of diverse and dynamic pedestrian interactions. This is further compounded by the varying environmental conditions in which these interactions take place. To ensure precise analysis, a substantial contextual understanding is essential. While existing methods have demonstrated promising performance in pedestrian anomaly detection, it is worth considering that GPT-4V, with its advanced contextual comprehension capabilities, has the potential to significantly enhance the performance of this task.

9.2 Testing philosophy

We utilize the GPT-4V model, which currently only accepts image format visual input, for pedestrian anomaly detection. To prompt the model, we select two images from the video dataset. In addition to the image prompt, we include a simple text prompt asking the model to determine if the video frames contain anomalies or outlier points and provide a specific reason if so.

9.3 Case Demonstration

In Fig. 33, we illustrate a scenario (from UCF-Crime dataset [85]) where a pedestrian aggresses another on the road. The GPT-4V model recognizes the aggressive behavior as an anomaly when compared to typical interactions. Additionally, it suggests caution due to the "LiveLeak" watermark, implying a need for further analysis with sufficient contextual information before drawing conclusions. The model's adeptness at discerning aggressive behavior, even in the absence of technical anomalies, demonstrates its potential to identify social anomalies within visual data.

10 Traffic Anomaly Detection

10.1 Task Introduction

Traffic anomaly detection primarily aims at identifying the commencement and conclusion of abnormal events, with lesser emphasis on spatial localization. Various methodologies [38, 70, 24, 67, 68, 35, 35] have been devised to model normalcy and discern regular patterns in video frames. The prevailing challenge for anomaly detection in traffic scenarios is the development of robust algorithms that can effectively differentiate between normal and abnormal vehicles and driving behaviors, thereby ensuring the safety and reliability of the autonomous vehicle system. Integrating GPT4v into traffic anomaly detection promises to refine the precision and speed of current systems. GPT4v, which has the ability to conduct high-level understanding, is adept at parsing the intricacies of traffic data, thereby sharpening the discrepancy between normal variations and true anomalies. This precision is critical for developing real-time monitoring systems that deliver accurate alerts while minimizing false positives.

10.2 Testing philosophy

We employ GPT-4V for traffic anomaly detection, which, as of now, only accepts visual input in image format. To engage the model, we select a representative image from the traffic scene, accompanied by a succinct text prompt. This prompt requests the model to ascertain whether the image frames harbor anomalies or outlier points, and if found, to elucidate the specific reasons for such irregularities.

10.3 Case Demonstration

As depicted in Fig. 34 and 35, by scrutinizing the spatial-temporal dynamics within the traffic scenes from a traffic anomaly detection dataset [48], GPT-4V proficiently differentiates between standard traffic flow and anomalous events. Beyond merely identifying outliers in traffic patterns, the model extends its utility by offering insightful elucidations concerning the abnormal nature of the scenarios. For instance, in Fig. 34, the model effectively explicates an abnormal vehicular maneuver that collides with the roadside barrier and deviates from typical driving behavior. Harnessing its deep comprehension of the underlying patterns and relationships within the traffic data, the model employs interpretable techniques to unravel the factors contributing to the anomaly, thereby providing a nuanced understanding that could be pivotal for enhancing the safety and reliability of autonomous driving systems.

11 Time Series Anomaly Detection

11.1 Task Introduction

Time series anomaly detection refers to the task of identifying unusual or abnormal patterns, events, or behaviors in sequential data over time, that deviate significantly from the expected or normal behavior. Time series anomaly detection models can be categorized as supervised or unsupervised algorithms. Supervised methods perform well when anomaly labels are available, such as AutoEncoder [79] and RobustTAD[34]. Unsupervised algorithms are suitable when obtaining anomaly labels is challenging. This has led to the development of new unsupervised methods, including DAGMM [115] and OmniAnomaly [83]. Unsupervised deep learning methods excel in time series anomaly detection, leveraging representation learning and a reconstruction approach to accurately identify anomalies without the need for labeled data [110, 47, 108].

11.2 Testing philosophy

To exploit GPT-4V for time series anomaly detection, we plot time series into images and then deliver the testing data to GPT-4V. Specifically, we select two instances [2, 89] along with a simple text prompt asking the model to determine if the image contains anomalies or outlier points and provide a specific reason if so.

11.3 Case Demonstration

As illustrated in Fig. 36 and 37, by examining the temporal dependencies and trends within the time series, GPT-4V adeptly differentiates between normal fluctuations and anomalous behavior. Beyond merely detecting outliers in the time series curves, the model extends its utility by offering insightful explanations regarding the abnormal nature of the data. For instance, in Fig. 37, the model effectively elucidates the abnormal peak in the time series. Drawing upon its profound understanding of the underlying patterns and relationships within the data, the model employs interpretability techniques to illuminate the factors contributing to the anomaly.

12 Prospect

The future evaluation and utilization of GPT-4V for anomaly detection hold significant promise in addressing complex challenges across various domains. As a versatile language model, GPT-4V demonstrates its potential in anomaly detection, and the following prospects aim to refine its capabilities, foster integration, and elevate its performance.

1. **Quantitative Analysis:** Incorporating quantitative metrics, such as Precision, Recall, and F1-score, alongside AUC-ROC and MAP, in future evaluations will provide a more comprehensive understanding of GPT-4V's anomaly detection performance. This quantification will empower a more objective assessment of the model's capabilities and its adaptation to diverse anomaly detection tasks.
2. **Expanding Evaluation Scope:** Expanding the scope to include real-world challenges, such as varying lighting conditions and occlusions in image-based anomaly detection, and different types of anomalies in time-series data, offers a more realistic view of GPT-4V's adaptability and limitations. The inclusion of synthetic and real-world anomalies adds depth to the evaluation process.

3. **Multi-round Interaction Evaluation:** The potential of multi-round conversations for GPT-4V's iterative learning and adaptation to feedback provides a dynamic framework for enhancing its performance in anomaly detection. It is a promising avenue for scenarios where ongoing refinement is crucial, such as cybersecurity.
4. **Incorporation of Human Feedback:** Utilizing human feedback loops presents the opportunity for domain experts to refine GPT-4V's understanding of complex or nuanced anomalies. The collaboration between the model and experts promises to address real-world challenges effectively.
5. **Integration of Auxiliary Data:** Exploring the impact of integrating auxiliary data, such as additional sensor readings or metadata, is instrumental in enhancing GPT-4V's understanding and accuracy in identifying anomalies across various domains. This comprehensive approach aligns with real-world data scenarios.
6. **Comparison with Specialized Models:** Comparative evaluations against specialized anomaly detection models are essential to identify the specific strengths and weaknesses of GPT-4V. These assessments will clarify the domains and use cases where GPT-4V's versatility excels or where specialized models remain superior.
7. **Real-Time Performance Assessment:** Evaluating GPT-4V's real-time performance is crucial for applications requiring rapid anomaly detection. This prospect ensures the model's suitability for time-critical or online anomaly detection tasks.
8. **Transfer Learning Evaluation:** Assessing the effectiveness of transfer learning in fine-tuning GPT-4V for specific anomaly detection tasks can pave the way for broader generalization. It enhances the model's adaptability in diverse anomaly detection scenarios.
9. **Hybrid Model Development:** The development of hybrid models combining GPT-4V with other machine learning or deep learning approaches offers an innovative approach to address anomaly detection challenges. These hybrids aim to leverage GPT-4V's linguistic capabilities while enhancing its performance in specialized scenarios.

In summation, these prospects set the stage for a comprehensive and multifaceted exploration of GPT-4V's anomaly detection potential. By combining quantitative metrics, real-world challenges, human feedback, auxiliary data integration, comparative assessments, and real-time capabilities, we can unlock the full scope of GPT-4V's utility in addressing anomalies across diverse fields. The journey towards improved anomaly detection with GPT-4V is one of collaboration, adaptation, and innovation, promising exciting developments in the years to come.

13 Conclusion

In conclusion, the assessment of GPT-4V's capabilities in anomaly detection signifies a notable advancement in the realm of versatile and adaptable AI models. GPT-4V demonstrates exceptional proficiency in identifying anomalies across diverse modalities and fields, offering both comprehensive and nuanced semantic comprehension. Its ability to deduce anomalies and its responsiveness to an expanding array of prompts underscore its versatility and potential. Nevertheless, like any technology, there remains room for further enhancement, particularly in intricate and subtle scenarios.

The opportunities delineated in this evaluation propose promising avenues for future research and development. The inclusion of quantitative metrics, broadening the spectrum of evaluations, embracing human input, and integrating supplementary data all contribute to augmenting the performance of GPT-4V. Comparative assessments against specialized models and the exploration of hybrid models further enrich the landscape of anomaly detection. Real-time assessment and the incorporation of transfer learning hold the promise of addressing time-sensitive situations and generalizing anomaly detection across diverse domains.

As we embark on this journey to unlock the full potential of GPT-4V, collaboration, adaptability, and innovation will serve as the foundational pillars of our success. The evaluation and utilization of GPT-4V for anomaly detection do not merely signify an exploration of technology but also serve as a testament to the ongoing evolution of AI and its transformative impact on real-world applications. Keeping these prospects in mind, the future of anomaly detection holds significant promise, and GPT-4V stands at the forefront of this captivating evolution.

Industrial Image Anomaly Detection: Case1

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The second image shows a **braided or twisted element** that is not present in the first image. This can be considered an anomaly or defect, depending on the intended use or design of the object in question.



One-shot (with class information)

Language Prompt

The first image given about the **bottle** is normal. Please determine whether the second image given about the **bottle** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon comparing the two images: The first image shows the bottle's opening with a clean and even edge. The second image displays an anomaly near the bottle's opening. Specifically, there seems to be a foreign object or material, possibly a piece of string or debris, protruding into the bottle's opening. In conclusion, the second image of the bottle contains an anomaly, which is the presence of a foreign object or material near the bottle's opening.

One-shot (with human expertise)

Prompt

The first image given about the **bottle** is normal. Please determine whether the second image given about the **bottle** contains anomalies or defects. If yes, give a specific reason. **Normally, the image given should depict clear and identifiable bottles. It may have defects such as broken parts, contaminations.**

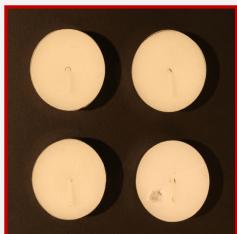
GPT-4V

Upon examination of the second image, there appears to be an anomaly in the form of a foreign object or contamination inside the bottle, resembling a braided or twisted material. This is not present in the first image and is not typical for a clear and identifiable bottle. Thus, the second image of the bottle contains a defect.

Figure 3 | Industrial Image Anomaly Detection: Case 1, one-shot, the Bottle category of MVTec AD [6]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Detection: Case2

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

1. The top left candle has a slight mark or imperfection near the top.
 2. The bottom right candle has a noticeable defect or indentation around the wick area.
- So, yes, there are anomalies or defects in the image, specifically on the top left and bottom right candles.

Zero-shot (with class information)

Language Prompt

Please determine whether the image given about the **candle** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

1. The top left and top right candles appear to be in normal condition with their wicks intact.
 2. The bottom left candle has a slightly tilted wick.
 3. The bottom right candle has a noticeable defect. The wax surrounding the wick appears to be damaged or melted in an irregular manner.
- Thus, there is at least one anomaly or defect observed in the set of candles, specifically with the bottom right candle due to its irregular wax condition near the wick.

Zero-shot (with human expertise)

Prompt

Please determine whether the image given about the **candle** contains anomalies or defects. If yes, give a specific reason. **Normally, the image given should display four round, flat candles with centered wicks. It may have defects such as uneven wax surfaces, discolored patches, or misaligned wicks.**

GPT-4V

The image displays four round, flat candles. Upon examination, the following anomalies or defects are observed:

1. The bottom right candle has a noticeable indentation or damaged area near its wick.
2. The bottom left candle's wick appears to be slightly slanted. The other two candles at the top seem to be consistent with the described normal appearance.

Figure 4 | Industrial Image Anomaly Detection: Case 2, zero-shot, the Candle category of VisA [116]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Detection: Case2

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The second image does contain anomalies or defects. Specifically, the bottom right candle has a noticeable deformity or damage near its wick.

One-shot (with class information)

Language Prompt

The first image given about the **candle** is normal. Please determine whether the second image given about the **candle** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Yes, the second image contains anomalies or defects. Specifically, the bottom right candle has a noticeable chunk missing or damaged near its wick.

One-shot (with human expertise)

Prompt

The first image given about the **candle** is normal. Please determine whether the second image given about the **candle** contains anomalies or defects. If yes, give a specific reason. Normally, the image given should display four round, flat candles with centered wicks. It may have defects such as uneven wax surfaces, discolored patches, or misaligned wicks.

GPT-4V

Upon examining the second image of the candles, I can observe the following anomalies or defects: 1. The bottom-right candle has a visible hole or indentation near the wick, which is not present in the other candles. 2. The bottom-left candle's wick appears to be slightly slanted compared to the others. These observations indicate that the second image does contain some anomalies or defects in comparison to the typical appearance of the candles as described.

Figure 5 | Industrial Image Anomaly Detection: Case 2, one-shot, the Candle category of VisA [116]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Detection: Case3

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The image shows an HC-SR04 ultrasonic sensor. Upon examination, **the board and components appear to be in good condition without noticeable anomalies or defects.** The soldering looks neat, and there are no visible signs of physical damage, burns, or missing components.

Zero-shot (with class information)

Language Prompt

Please determine whether the image given about the **PCB** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Based on the provided image of the PCB: **There don't appear to be any major visible anomalies or defects on the surface. The soldering points look consistent, and the labeling is clear. The ultrasonic sensor (HC-SR04) seems to be properly seated.**

Zero-shot (with human expertise)

Prompt

Please determine whether the image given about the **PCB** contains anomalies or defects. If yes, give a specific reason. **Normally, the image given should show a clean and well-structured printed circuit board (PCB) with clear traces, soldered components, and distinct labels. It may have defects such as bent pins, cold solder joints, missing components, or smudged labels.**

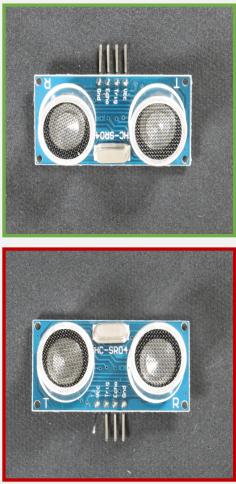
GPT-4V

Upon inspection: - The printed labels such as "HC-SR04", "VCC", "Trig", "Echo", "Gnd", etc., are clear and distinct, which is a good sign. - The soldering on the pins appears uniform and without any obvious cold solder joints. - There are no visible missing components, lifted traces, or smudged labels. From the viewable portion in the image, I don't see any obvious anomalies or defects.

Figure 6 | Industrial Image Anomaly Detection: Case 3, zero-shot, the PCB2 category of VisA [116]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Detection: Case3

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon comparing the two images, both appear to be of the same HC-SR04 ultrasonic sensor module. **No noticeable anomalies or defects are evident in the second image compared to the first.** Both images seem to be consistent in terms of components and layout.

One-shot (with class information)

Language Prompt

The first image given about the **PCB** is normal. Please determine whether the second image given about the **PCB** contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon examining the second image of the PCB: The PCB appears to be an ultrasonic distance sensor, likely an HC-SR04 module. On closer inspection of the second image, there's a slight observation to be made: **There seems to be a soldering inconsistency or excess solder on the pin labeled "Gnd" (Ground). The solder appears to be a bit more bulged compared to the other pins.**

One-shot (with human expertise)

Prompt

The first image given about the **PCB** is normal. Please determine whether the second image given about the **PCB** contains anomalies or defects. If yes, give a specific reason. **Normally, the image given should show a clean and well-structured printed circuit board (PCB) with clear traces, soldered components, and distinct labels. It may have defects such as bent pins, cold solder joints, missing components, or smudged labels.**

GPT-4V

After closely examining the second image of the PCB: I can confirm that the board appears to be clean, and the labels are clear. **The soldering appears to be uniform, and there are no visible bent pins, cold solder joints, missing components, or smudged labels.** Based on this observation, the second image does not seem to contain any anomalies or defects.

Figure 7 | Industrial Image Anomaly Detection: Case 3, one-shot, the PCB2 category of VisA [116]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Localization: Case1

Image Prompt



Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Based on the comparison between the first and second images:

1. The region marked as "1" in the second image indicates a possible defect or anomaly on the inner rim of the object. It seems like there's a slight irregularity or imperfection in that area.
2. The region marked as "2" highlights the twisted or braided cord or wire. It's not clear from the image alone whether this is an intended feature or a defect. However, since it's specifically marked, it might indicate that there's something notable about it. In summary, there are potential anomalies in the areas marked as "1" and "2", with the first being a possible imperfection on the inner rim, and the second being related to the cord or wire.

Figure 8 | Industrial Image Anomaly Localization: Case 1, zero-shot, the Bottle category of MVTec AD [6]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Localization: Case2

Image Prompt



Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon inspection of the first image and cross-referencing with the second image's markings: 1. Area labeled "1": This region shows the transition between two different textures or surfaces of the object. While it is not necessarily an anomaly or defect by itself, it could be an indication of where the object began to form or where two different materials or layers meet. 2. Area labeled "2": This region clearly shows a hole or break in the surface of the object. This can be classified as a defect or anomaly, as it interrupts the continuous surface of the object and appears to be an unintentional damage. In conclusion, the object contains at least one definite anomaly or defect, which is the hole or break in the surface (Area labeled "2").

Figure 9 | Industrial Image Anomaly Localization: Case 2, the Hazelnut category of MVTec AD [6]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Industrial Image Anomaly Detection: Case3

Image Prompt



Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the image contains anomalies or defects. If yes, give a specific reason.

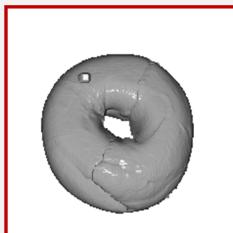
GPT-4V

Upon inspection of the provided images: - Number 16 has a highlighted oval around it. Upon comparison with the first image, this pill appears to have some kind of smudge or discoloration on its surface, indicating a potential defect. - Number 15 is highlighted with a blue oval, which might be used to indicate a different type of anomaly compared to the yellow ovals. However, without further context on what the blue oval specifically signifies, it's challenging to pinpoint an exact defect. Upon visual inspection of the first image, this pill seems relatively normal. - The rest of the pills with numbers (1-20, excluding 15 and 16) don't seem to have any distinct visible defects upon visual comparison with the first image. **In conclusion, only pill number 16 displays a clear potential defect or anomaly based on the provided images.** Pill number 15, highlighted with a blue oval, might have a different type of anomaly, but without additional context, it's hard to determine the exact issue.

Figure 10 | Industrial Image Anomaly Localization: Case 3, the Capsule category of VisA [116]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case1

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

There are a few notable irregularities: 1. There's a small protrusion or bump on the top left part of the torus. 2. There are some irregular surfaces or rough patches, especially in the central hole area.

Zero-shot (with class information)

Language Prompt

Please determine whether the rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason.

GPT-4V

There seem to be some anomalies or inconsistencies in the depth data: 1. There's a significant dent or indentation on the left side of the bagel. 2. There are smaller inconsistencies and rough patches on the surface of the bagel, particularly towards the center hole area.

Zero-shot (with human expertise)

Prompt

Please determine whether the rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded shape with a central hole, consistent with the typical form of a bagel. It may have defects such as irregularities in the surface texture, inconsistencies in the hole's shape, or uneven thickness throughout the structure.

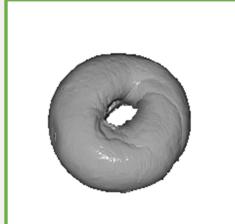
GPT-4V

Based on the provided depth image of the bagel: 1. There are noticeable irregularities on the surface of the bagel, particularly a few bumps and depressions. 2. The hole in the center appears to be somewhat inconsistent in shape, with one side appearing more compressed than the other. 3. There's a noticeable defect or anomaly on the top side of the bagel, appearing as a small raised region.

Figure 11 | Point Cloud Anomaly Detection: Case 1, zero-shot, the Bagel category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case1

Image Prompt

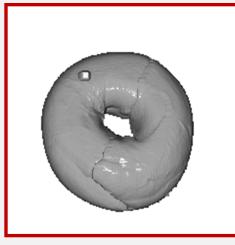


One-shot (naive)

Language Prompt

The first rendered depth image is normal. Please determine whether the second rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V



The second rendered depth image does contain anomalies. Specifically, there are irregularities and artifacts present on the surface, as seen by the uneven patches and the small protrusion or bump on the upper portion.

One-shot (with class information)

Language Prompt

The first rendered depth image given about the bagel is normal. Please determine whether the second rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Based on the images provided, the first rendered depth image of the bagel appears consistent throughout its structure. However, the second image exhibits some irregularities, specifically what appear to be indentations or voids on the surface of the bagel.

One-shot (with human expertise)

Prompt

The first rendered depth image given about the bagel is normal. Please determine whether the second rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded shape with a central hole, consistent with the typical form of a bagel. It may have defects such as irregularities in the surface texture, inconsistencies in the hole's shape, or uneven thickness throughout the structure..

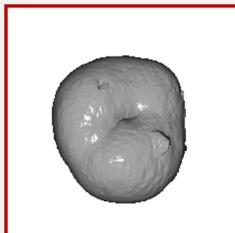
GPT-4V

The second image does show some anomalies when compared to the first image and your provided description. There appear to be some irregularities on the surface, particularly what seems to be a protrusion or lump near the top.

Figure 12 | Point Cloud Anomaly Detection: Case 1, one-shot, the Bagel category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case2

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The rendered depth image appears to have some irregularities or noise, visible as bright specks scattered throughout. This might be considered as anomalies or defects depending on the intended use of the image.

Zero-shot (with class information)

Language Prompt

Please determine whether the rendered depth image given about the peach contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Based on the provided depth image, there appear to be irregularities or anomalies on the surface of the peach, as seen by the white areas. These areas might represent indentations, protrusions, or other surface defects in the peach.

Zero-shot (with human expertise)

Prompt

Please determine whether the rendered depth image given about the peach contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded, smooth surface characteristic of a peach. It may have defects such as dents, uneven texture, or abnormalities in its contour.

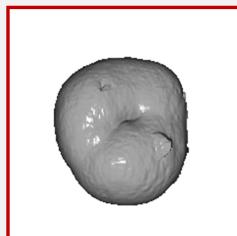
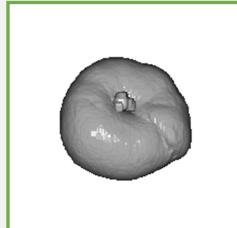
GPT-4V

There are some observable irregularities: 1. There are regions on the surface that appear to have uneven texture or depressions, which can be interpreted as potential dents or imperfections. 2. Some areas on the peach seem to have sharper changes in depth, suggesting an uneven contour or surface anomalies.

Figure 13 | Point Cloud Anomaly Detection: Case 2, zero-shot, the Peach category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case2

Image Prompt



One-shot (naive)

Language Prompt

The first rendered depth image is normal. Please determine whether the second rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon examining the second rendered depth image, it appears to be similar in structure to the first. However, the second image seems to have some artifacts or irregularities, especially noticeable as white patches/spots scattered across the surface.

One-shot (with class information)

Language Prompt

The first rendered depth image given about the peach is normal. Please determine whether the second rendered depth image given about the peach contains anomalies or defects. If yes, give a specific reason.

GPT-4V

In the second image, there are some noticeable differences compared to the first. Specifically, there appear to be irregularities or indentations on the surface of the peach that were not present in the first image.

One-shot (with human expertise)

Prompt

The first rendered depth image given about the peach is normal. Please determine whether the second rendered depth image given about the peach contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded, smooth surface characteristic of a peach. It may have defects such as dents, uneven texture, or abnormalities in its contour.

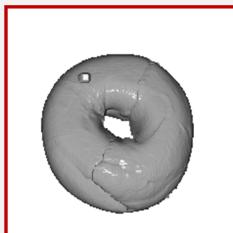
GPT-4V

Examining the second rendered depth image of the peach, it appears to have some anomalies when compared to the expected characteristics of a typical peach. There are noticeable irregularities in the surface texture and contour of the peach, making it appear uneven and not smooth. Specifically, there seem to be indentations or dents present.

Figure 14 | Point Cloud Anomaly Detection: Case 2, one-shot, the Peach category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case1

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

There are a few notable irregularities: 1. There's a small protrusion or bump on the top left part of the torus. 2. There are some irregular surfaces or rough patches, especially in the central hole area.

Zero-shot (with class information)

Language Prompt

Please determine whether the rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason.

GPT-4V

There seem to be some anomalies or inconsistencies in the depth data: 1. There's a significant dent or indentation on the left side of the bagel. 2. There are smaller inconsistencies and rough patches on the surface of the bagel, particularly towards the center hole area.

Zero-shot (with human expertise)

Prompt

Please determine whether the rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded shape with a central hole, consistent with the typical form of a bagel. It may have defects such as irregularities in the surface texture, inconsistencies in the hole's shape, or uneven thickness throughout the structure.

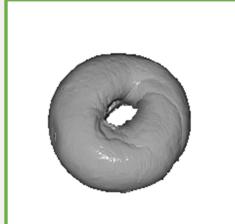
GPT-4V

Based on the provided depth image of the bagel: 1. There are noticeable irregularities on the surface of the bagel, particularly a few bumps and depressions. 2. The hole in the center appears to be somewhat inconsistent in shape, with one side appearing more compressed than the other. 3. There's a noticeable defect or anomaly on the top side of the bagel, appearing as a small raised region.

Figure 15 | Point Cloud Anomaly Detection: Case 3, zero-shot, the Rope category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Point Cloud Anomaly Detection: Case1

Image Prompt



One-shot (naive)

Language Prompt

The first rendered depth image is normal. Please determine whether the second rendered depth image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The second rendered depth image does contain anomalies. Specifically, there are irregularities and artifacts present on the surface, as seen by the uneven patches and the small protrusion or bump on the upper portion.

One-shot (with class information)

Language Prompt

The first rendered depth image given about the bagel is normal. Please determine whether the second rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Based on the images provided, the first rendered depth image of the bagel appears consistent throughout its structure. However, the second image exhibits some irregularities, specifically what appear to be indentations or voids on the surface of the bagel.

One-shot (with human expertise)

Prompt

The first rendered depth image given about the bagel is normal. Please determine whether the second rendered depth image given about the bagel contains anomalies or defects. If yes, give a specific reason. Normally, the image given should depict a rounded shape with a central hole, consistent with the typical form of a bagel. It may have defects such as irregularities in the surface texture, inconsistencies in the hole's shape, or uneven thickness throughout the structure..

GPT-4V

The second image does show some anomalies when compared to the first image and your provided description. There appear to be some irregularities on the surface, particularly what seems to be a protrusion or lump near the top.

Figure 16 | Point Cloud Anomaly Detection: Case 3, one-shot, the Rope category of MVTec 3D [8]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Logical Anomaly Detection: Case1

Image Prompt



Zero-shot

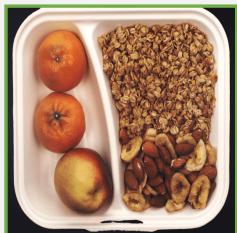
Language Prompt

The image given about breakfast boxes should obey the following rules: 1. It should contain two oranges, one peach, and some cereal, nuts, and banana slices; 2. The fruit should be on the left side of the lunch box, the cereal on the upper right, and the nuts and banana slices on the lower right of the lunch box. Please determine whether the given image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The placement of the items does not match the specified rules. The fruit should be on the left side, but they are on the right side in the provided image.

Image Prompt



One-shot

Language Prompt

The image given about breakfast boxes should obey the following rules: 1. It should contain two oranges, one peach, and some cereal, nuts, and banana slices; 2. The fruit should be on the left side of the lunch box, the cereal on the upper right, and the nuts and banana slices on the lower right of the lunch box. The first image meets all the standards and is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

It has two oranges and one peach on the left side, which complies with the specified requirements. The cereal is on the upper left, which is not as per the guidelines; it should be on the upper right. The nuts and banana slices are on the lower left, which is also incorrect; they should be on the lower right of the lunch box. Therefore, the second image has anomalies in the placement of the cereal, nuts, and banana slices.

Figure 17 | Logical Anomaly Detection: Case 1, the Breakfast Box category of MVTec LOCO [7]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Logical Anomaly Detection: Case2

Image Prompt



Zero-shot

Language Prompt

The image given about juice bottles should obey the following rules: 1. The juice type should match the label design. 2. To prevent bottle explosions, ensure the juice is filled to about 3cm below the bottle's opening. Please determine whether the given image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

1. The juice type appears to be represented by a label design showing bananas. The label reads "100% Juice", and the presence of bananas on the label suggests it's banana juice. 2. The juice level in the bottle is filled well below the bottle's opening. Without precise measurements, I can't determine the exact distance to the bottle's opening, but it appears to be more than 3cm. Based on the provided image and the rules you've given, there don't appear to be any anomalies or defects.

Image Prompt



One-shot

Language Prompt

The image given about juice bottles should obey the following rules: 1. The juice type should match the label design. 2. To prevent bottle explosions, ensure the juice is filled to about 3cm below the bottle's opening. The first image meets all the standards and is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

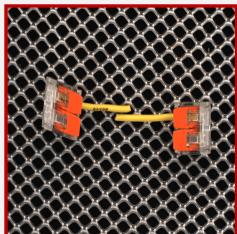
GPT-4V

The second image displays a bottle labeled with a banana design, indicating banana juice. Upon inspection: 1. The juice type matches the label design, as the bottle has a banana label on it. 2. Observing the level of the juice, it appears to be filled close to the top, with less than 3cm from the bottle's opening. Based on the criteria you provided, the second image contains an anomaly. Specifically, the juice is filled too close to the top and does not have the recommended 3cm space below the bottle's opening to prevent potential bottle explosions.

Figure 18 | Logical Anomaly Detection: Case 2, the Juice Bottle category of MVTec LOCO [7]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Logical Anomaly Detection: Case3

Image Prompt



Zero-shot

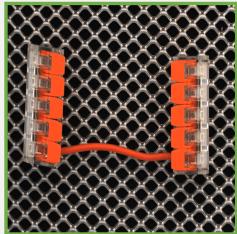
Language Prompt

The image given about splicing connectors should obey the following rules: 1. Both the left and right connectors must be of the same type. 2. A continuous cable should connect the two connectors. Please determine whether the given image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The image shows two splicing connectors on a background of a metal mesh. Based on the rules you provided: 1. Both the left and right connectors appear to be of the same type. 2. A continuous cable does connect the two connectors.

Image Prompt



One-shot

Language Prompt

The image given about splicing connectors should obey the following rules: 1. Both the left and right connectors must be of the same type. 2. A continuous cable should connect the two connectors. The first image meets all the standards and is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Examining the second image, I observe the following: 1. Both the left and right connectors are of the same type. 2. A continuous cable connects the two connectors. However, the cable is labeled "EVOKE."

Figure 19 | Logical Anomaly Detection: Case 3, the Splicing Connector category of MVTEC LOCO [7]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Logical Anomaly Detection: Case4

Image Prompt



Zero-shot

Language Prompt

The image given about **screw bags** should obey the following rules: 1. Includes two screws, two nuts, and two washers. 2. The screws should be of varying lengths: one long and one short. Please determine whether the given image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

The image displays a plastic bag containing hardware components. Based on your criteria: 1. I can see two screws, two nuts, and two washers in the bag, so it meets this requirement. 2. The screws appear to be of varying lengths with one being noticeably longer than the other.

Image Prompt



One-shot

Language Prompt

The image given about **screw bags** should obey the following rules: 1. Includes two screws, two nuts, and two washers. 2. The screws should be of varying lengths: one long and one short. The first image meets all the standards and is normal. Please determine whether the second image contains anomalies or defects. If yes, give a specific reason.

GPT-4V

Upon examining the second image: 1. There are two screws present, with one appearing longer than the other, fulfilling the requirement for screws of varying lengths. 2. There are three washers present instead of the required two. 3. There are two nuts, which meets the specified requirement.

Figure 20 | Logical Anomaly Detection: Case 4, the Screw Bag category of MVTec LOCO [7]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Chest X-Ray Case

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies. If yes, give a specific reason.

GPT-4V

The image appears to be a chest X-ray. From a cursory examination:

- The heart silhouette, diaphragm, and mediastinum appear within normal limits.
- The lung fields look mostly clear without obvious consolidations or masses.
- The bony structures, including the ribs and the visible parts of the spine, appear intact.

Zero-shot (with general medical information)

Language Prompt

Please determine whether this X-ray image on the chest contains any anomalies. If yes, please give your reason.

GPT-4V

The chest X-ray appears to show the lungs, ribs, and the heart. There might be some areas of increased opacity, which could suggest a variety of conditions including infections, inflammations, tumors, or other pathologies. However, the clarity of the image and the absence of multiple views (e.g., lateral view) make it challenging to provide a definitive answer.

Zero-shot (with human expertise)

Prompt

Please determine whether this chest x-ray image contains any anomalies. If yes, please give your reason. The image given should be classified as normal or pneumonia.

GPT-4V

Based on the image you provided, it appears there might be some haziness or opacities in the lung fields, which could be suggestive of pneumonia.

Figure 21 | Medical Anomaly Detection: Case 1, the Chest X-ray [49]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Chest X-Ray Case

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies. If yes, give a specific reason.

GPT-4V

Upon inspection of the second X-ray image, there appear to be some areas of increased opacity within the lung fields. This could indicate a variety of conditions such as infection, inflammation, or other pulmonary issues.

One-shot (with class information)

Language Prompt

The first image of Chest X-ray is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason.

GPT-4V

Upon observation of the second image, there appear to be areas of increased opacity in the lung fields, which can suggest various conditions such as infections, fluid accumulation, or other lung pathologies.

One-shot (with human expertise)

Prompt

The first image of Chest X-ray is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason. The image given should be classified as normal or pneumonia.

GPT-4V

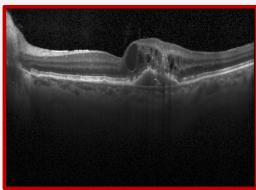
The first image, as you've mentioned, appears to be a normal chest X-ray with no obvious signs of pneumonia. The lungs seem clear, and the heart, diaphragm, and bony structures look typical.

Regarding the second image, there seem to be some patchy opacities, which might be consistent with infiltrates found in pneumonia. These opacities can be seen as hazier, less translucent areas.

Figure 22 | Medical Anomaly Detection: Case 1, the Chest X-ray [49]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: RetinaOCT Case

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains **anomalies**. If yes, give a specific reason.

GPT-4V

The image appears to be an OCT (Optical Coherence Tomography) scan, commonly used in ophthalmology to capture detailed cross-sectional images of the retina.

From the image provided, there seems to be some irregularities or disruptions in the retinal layers, especially towards the right side where there are hyper-reflective areas and possible cystic spaces.

Zero-shot (with general medical information)

Language Prompt

Please determine whether this **Retina OCT image** contains any **anomalies**. If yes, please give your reason.

GPT-4V

The image you provided appears to be an Optical Coherence Tomography (OCT) scan of a retina.

The different layers of the retina can be seen, with varying levels of reflectivity. There appears to be an area with increased reflectivity and potential thickening or elevation in the central region. This might suggest the presence of some fluid or structural change.

Zero-shot (with human expertise)

Prompt

Please determine whether this **Retina OCT image** contains any **anomalies**. If yes, please give your reason. The image given should **be classified as normal, drusen, diabetic macular edema or choroidal neovascularization**.

GPT-4V

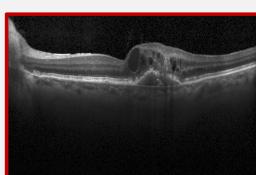
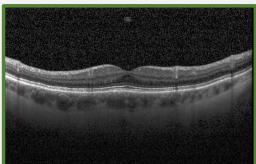
Based on the image provided, it appears to be a Retina OCT (Optical Coherence Tomography) scan. The scan seems to show some abnormalities in the retinal layers.

The presence of irregular elevations and hyper-reflective regions in the scan could suggest the presence of fluid or other abnormalities consistent with conditions like choroidal neovascularization or diabetic macular edema. The image appears to be more consistent with choroidal neovascularization **or diabetic macular edema** rather than a normal retina or drusen.

Figure 23 | Medical Anomaly Detection: Case 2, the Retinal OCT [49]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: RetinaOCT Case

Image Prompt



One-shot (naive)

Language Prompt

The first image is **normal**. Please determine whether the second image contains **anomalies**. If yes, give a specific reason.

GPT-4V

The images provided appear to be OCT (Optical Coherence Tomography) scans, which are commonly used in ophthalmology to capture detailed cross-sectional images of the retina. The first image appears to show a relatively smooth and consistent retinal layering; The second image, however, exhibits a pronounced disruption or irregularity in the retinal layers towards the right side. There's an area with hyperreflective foci and what looks like some kind of cystic or fluid-filled formation.

These observations suggest that the second image does contain anomalies compared to the first.

One-shot (with class information)

Language Prompt

The first image of Retina OCT is **normal**. Please determine whether the second image given contains anomalies. If yes, give a specific reason.

GPT-4V

The images provided appear to be Optical Coherence Tomography (OCT) scans of the retina.

The first image, as you mentioned, appears to be a normal OCT scan of the retina. The layers of the retina seem to be well-defined and no obvious pathology is evident.

The second image shows some irregularities and disruptions in the retinal layers. There are areas of hyper-reflectivity and potential cystoid spaces or edematous regions in the retinal tissue. These findings suggest potential retinal pathology such as cystoid macular edema or another form of retinal anomaly.

One-shot (with human expertise)

Prompt

The first image of Retina OCT is **normal**. Please determine whether the second image given contains anomalies. If yes, give a specific reason. The image given should be classified as **normal**, **drusen**, **diabetic macular edema** or **choroidal neovascularization**.

GPT-4V

The second image appears to have irregularities compared to the first. Specifically, there seem to be hyper-reflective regions and structural distortions within the retinal layers. This could be indicative of an anomaly.

From the provided options and based on the appearance, the second image seems to show signs consistent with **choroidal neovascularization (CNV)**. CNV is characterized by the growth of new blood vessels originating from the choroid through breaks in Bruch's membrane into the sub-retinal or sub-retinal pigment epithelium space.

Figure 24 | Medical Anomaly Detection: Case 2, the Retinal OCT [49]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Head CT Case

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies. If yes, give a specific reason.

GPT-4V

The image you've provided appears to be an axial (cross-sectional) view from a computed tomography (CT) scan of a human head.

There seems to be a hyperdense (brighter) region on one side of the brain, which could suggest a potential anomaly such as a hemorrhage, mass, or another type of lesion. The asymmetry between the two hemispheres is noticeable, and typically, structures in the brain are symmetrical.

Zero-shot (with general medical information)

Language Prompt

Please determine whether this head CT image contains any anomalies. If yes, please give your reason.

GPT-4V

It appears there might be a hyperdense region on one side of the brain, which could suggest a potential hemorrhage or another type of lesion. The asymmetry between the two hemispheres is noticeable.

Zero-shot (with human expertise)

Prompt

Please determine whether this head CT image contains any anomalies. If yes, please give your reason. The image given should be classified as normal or hemorrhage.

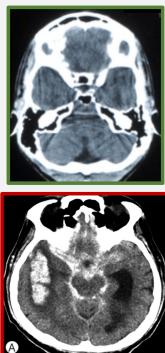
GPT-4V

Based on the image provided, it seems there might be areas of increased density on the right side of the brain (left side of the image as it's presented). These areas of increased density could possibly be indicative of hemorrhage.

Figure 25 | Medical Anomaly Detection: Case 3, the Head CT [51]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Head CT Case

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies. If yes, give a specific reason.

GPT-4V

The second image appears to have some areas of increased radiodensity, particularly in the central region of the brain. These could potentially be indicative of some pathology, such as an infarction, hemorrhage, or a mass.

One-shot (with class information)

Language Prompt

The first image of head CT is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason.

GPT-4V

The second image appears to be an axial view of a head CT scan. It does seem to show some differences compared to a typical normal head CT scan. Notably, there are areas of hypodensity, or darker regions, which may suggest the presence of edema, ischemia, or other pathological processes. Additionally, there might be some asymmetry in the appearance of the brain structures.

One-shot (with human expertise)

Prompt

The first image of head CT is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason. The image given should be classified as normal or hemorrhage.

GPT-4V

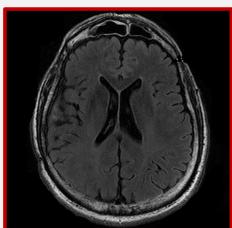
The second image appears to show hyperdense areas within the brain tissue, which could be indicative of hemorrhage. Compared to the surrounding brain tissue, these areas are brighter or more "white." This is in contrast to the first image, which you've described as normal and which lacks these hyperdense regions.

Based on the second image provided, it can be classified as "hemorrhage."

Figure 26 | Medical Anomaly Detection: Case 3, the Head CT [51]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Head MRI Case

Image Prompt



Zero-shot (naive)

Language Prompt

Please determine whether the image contains anomalies. If yes, give a specific reason.

GPT-4V

The image you provided appears to be an axial MRI of the brain. The image shows a symmetrical appearance of the brain structures, with clear differentiation between the gray and white matter. The ventricles appear normal in size.

Zero-shot (with general medical information)

Language Prompt

Please determine whether this brain MRI image contains any anomalies. If yes, please give your reason.

GPT-4V

The image you provided appears to be an axial view of a brain MRI. From a non-clinical perspective, the image seems to display bilateral symmetry, which is generally a good sign.

Zero-shot (with human expertise)

Prompt

Please determine whether this brain MRI image contains any anomalies. If yes, please give your reason. The image given should be classified as normal or with tumor.

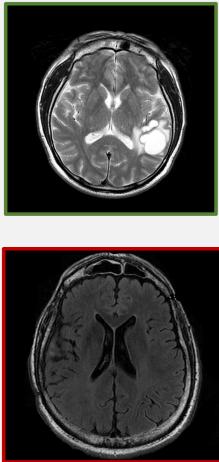
GPT-4V

From the image provided, it looks like a coronal view of a brain MRI. It appears to be relatively symmetrical, and I don't immediately notice any obvious masses or lesions that might suggest a tumor.

Figure 27 | Medical Anomaly Detection: Case 4, Head MRI Image [18]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Detection: Head MRI Case

Image Prompt



One-shot (naive)

Language Prompt

The first image is normal. Please determine whether the second image contains anomalies. If yes, give a specific reason.

GPT-4V

The images provided appear to be MRI scans of the brain in axial view. The first one indeed looks like a typical representation of a normal brain MRI in a T2-weighted sequence, where the cerebrospinal fluid (CSF) appears bright and the brain tissue appears in shades of gray.

In the second image, there's an apparent increased dark signal (hypointense) in the white matter regions on both sides. This could be indicative of several conditions. Some possible causes for such a pattern could be related to ischemia, demyelinating diseases, or certain types of metabolic disorders.

One-shot (with class information)

Language Prompt

The first image of head MRI is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason.

GPT-4V

In the second image, there appears to be an area of hyperintensity (increased brightness) in the white matter of the brain compared to the surrounding tissue. This could be indicative of an abnormality.

One-shot (with human expertise)

Prompt

The first image of head MRI is normal. Please determine whether the second image given contains anomalies. If yes, give a specific reason. The image given should be classified as normal or with tumor.

GPT-4V

The second image seems to display an MRI scan of a brain. Comparatively, there appears to be an abnormal hyperintense region in the brain, which could suggest the presence of a lesion or tumor.

Figure 28 | Medical Anomaly Detection: Case 4, Head MRI Image [18]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Localization: Abdominal CT Case

Image Prompt



Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the first image contains anomalies or defects. If yes, give a specific reason

GPT-4V

You've provided two images: the first is an unmarked CT scan, and the second is the same image with two areas highlighted.

In the second image, the following areas are marked:

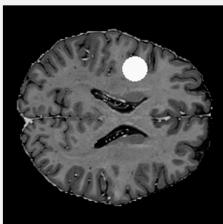
1. In the circled region, there appears to be a hyperdense area, which could be indicative of a variety of things such as calcification, a foreign body, or other types of pathology depending on the clinical context. This requires further clinical correlation to determine the significance.
2. The boxed region is within the soft tissue of what appears to be the thigh. This could represent an area of interest, possibly due to abnormal tissue density, presence of an object or lesion, or other pathology.

Overall, these marked areas could represent anomalies or defects in the context of the CT scan, but determining the exact nature and significance of these findings would require input from a medical professional with access to the full clinical picture, including symptoms, history, and potentially additional imaging or tests.

Figure 29 | Medical Anomaly Localization: Case 1, Abdominal CT Localization [114]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Localization: Head MRI Case

Image Prompt

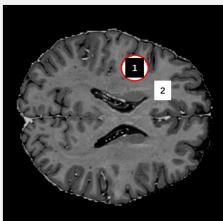


Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the first image contains anomalies or defects. If yes, give a specific reason

GPT-4V

The images you've provided appear to be MRI scans of a human brain. In the second image, you've marked two areas:



1. The area within the red circle seems to be the focus of interest. If this is an MRI scan, this area might be of concern due to its appearance being different from the surrounding tissue, suggesting it could be an anomaly.
2. The label '2' appears to be pointing to a region outside the brain, perhaps the skull or the surrounding space, which generally should not be the area of interest for brain anomalies.

Figure 30 | Medical Anomaly Localization: Case 2, Head MRI Localization [114]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Localization: Skin Lesion Case

Image Prompt



Language Prompt

The first image needs to be inspected. The second image contains its corresponding marks. Please determine whether the first image contains anomalies or defects. If yes, give a specific reason

GPT-4V

The images provided appear to be dermatological in nature, specifically they look like dermoscopic images of a skin lesion.

In the first image, we can see a skin lesion with varying colors and a non-uniform shape. There are different shades of brown and tan, and the distribution of the pigment is not symmetrical. Additionally, there are areas within the lesion where the color is more concentrated, and there are irregular borders.

The second image has an overlay with a numbered key:

1. The area marked as '1' is highlighted with a dotted red line encompassing the lesion, which seems to correspond to the irregularly shaped, colored area of the skin lesion.
2. The label '2' doesn't correspond to any particular feature within the dotted line but is placed outside the marked area, likely to indicate the area of normal skin surrounding the lesion.

Based on the analysis of the first image and the corresponding marked areas in the second image, the anomalies or defects in the lesion could be suggestive of atypical features often associated with skin malignancies such as melanoma. Key atypical features that might be concerning include:

Asymmetry of shape\Border irregularity\Color variation.

Diameter (if it's larger than 6mm, which can't be determined without a scale).

Figure 31 | Medical Anomaly Localization: Case 3, Skin Lesion Localization [26]. Yellow highlights the given class information and normal and abnormal state descriptions. Green, red, and blue highlight the expected, incorrect, and additional information outputted by GPT-4V.

Medical Anomaly Localization: Endoscopy Case

Image Prompt



Language Prompt

The first image needs to be inspected. **The second image contains its corresponding marks.** Please determine whether the first image contains anomalies or defects. If yes, give a specific reason

GPT-4V

The images appear to be from an endoscopic procedure, which is used to visually examine an internal organ or tissue in detail. It seems to be a **gastrointestinal endoscopy** based on the appearance of the mucosa and the structures visible.

In the second image, two areas are marked:

1. Area 1 is on a section of mucosa that looks generally smooth and continuous, without any obvious abnormalities at the resolution provided.
2. Area 2 highlights a rounded structure that appears to be protruding from the mucosal surface. **This could potentially be a polyp, which is a growth of tissue that can be benign or malignant.**

Figure 32 | Medical Anomaly Localization: Case 4, Endoscopy Localization [11]. **Yellow** highlights the given class information and normal and abnormal state descriptions. **Green**, **red**, and **blue** highlight the expected, incorrect, and additional information outputted by GPT-4V.

Pedestrian Anomaly Detection

Image Prompt



Language Prompt

Please determine whether the video frames contains anomalies or outlier points. If yes, give a specific reason.

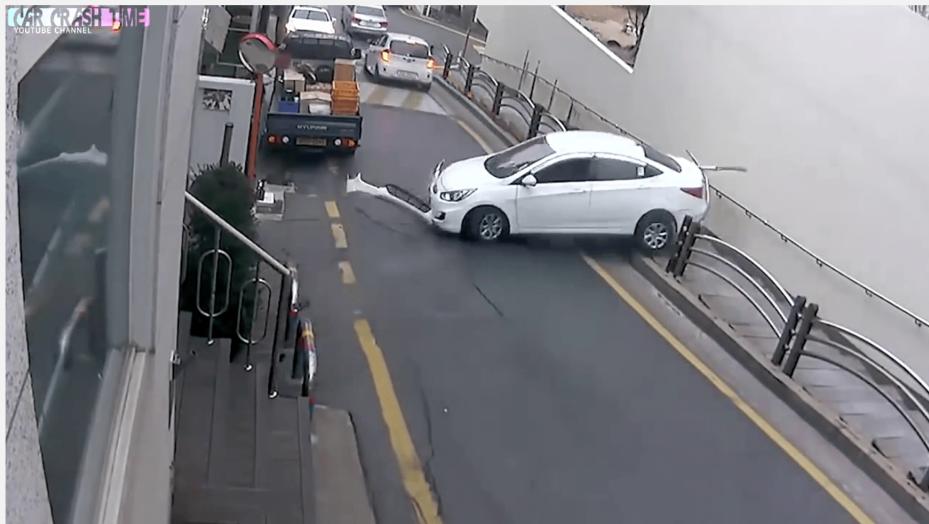
GPT-4V

From the still frames provided, there are no technical anomalies like distortions or pixelation evident. However, the content of the images seems to depict a physical altercation or some form of aggressive behavior between individuals. This can be considered an "anomaly" or "outlier" when comparing to regular, non-confrontational human interactions. It's important to approach this content with caution and context, especially given the "LiveLeak" watermark, which is a platform known for hosting graphic and shocking videos. If analyzing the content further, one should ensure they have all necessary context and information before drawing conclusions.

Figure 33 | Pedestrian Anomaly Detection: Case 1, from UCF-Crime Dataset [85]. Green highlights the expected information outputted by GPT-4V.

Traffic Anomaly Detection: Case1

Image Prompt



Language Prompt

Please determine whether the image contains anomalies or outliner points. If yes, give a specific reason.

GPT-4V

The image appears to capture a traffic scene with multiple vehicles. There are several potential anomalies or outlying points in the image: The most notable anomaly is the white car on the right side of the image, which seems to have collided with the roadside barrier or railing, causing a part of its front bumper to detach and fall onto the road. The truck in the center of the image has its rear portion slightly extending into another lane, which could pose a hazard for oncoming traffic. The watermark "CAR CRASH TIME" along with the "YOUTUBE CHANNEL" text on the top left corner indicates that the image might be from a video documenting car accidents or mishaps, further emphasizing the likelihood of anomalies in the scene. These points stand out as deviations from what would be considered a normal, uneventful traffic scene.

Figure 34 | Traffic Anomaly Detection: Case 1, from Kaggle Accident Detection [48]. Green highlights the expected information outputted by GPT-4V.

Traffic Anomaly Detection: Case2

Image Prompt



Language Prompt

Please determine whether the image contains anomalies or outlier points. If yes, give a specific reason.

GPT-4V

The image depicts a street scene with several vehicles and pedestrians. Upon examination, the following anomalies or outlier points can be identified:

Vehicle Positioning: The white car on the right side of the image seems to be stopped or parked in an unusual position. It's not in a designated parking spot and appears to be close to the crosswalk.

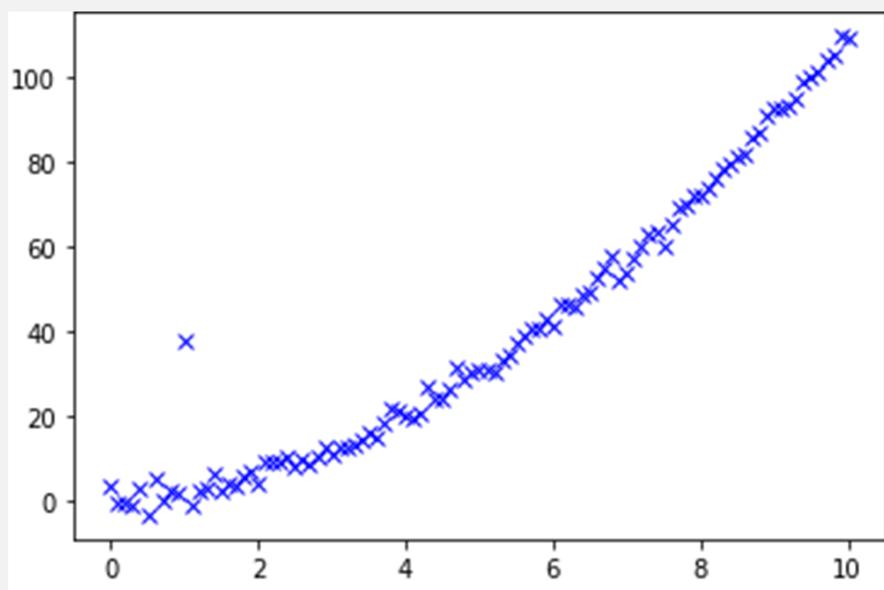
Pedestrian Behavior: Two individuals are standing next to the aforementioned white car. Their position is unusual, as they are not on the sidewalk and seem to be interacting with the car in the middle of the street.

Watermark: The image has a watermark "CRASH TIME" and "YouTube Channel" in the top corners. This could indicate that the image is taken from a video that captures traffic incidents or anomalies. These points deviate from what might be considered 'normal' behavior or conditions in a typical street scene, making them anomalies or outliers in this context.

Figure 35 | Traffic Anomaly Detection: Case 2, from Kaggle Accident Detection [48]. Green highlights the expected information outputted by GPT-4V.

Time-series Anomaly Detection: Case1

Image Prompt



Language Prompt

Please determine whether the image contains anomalies or outlier points. If yes, give a specific reason.

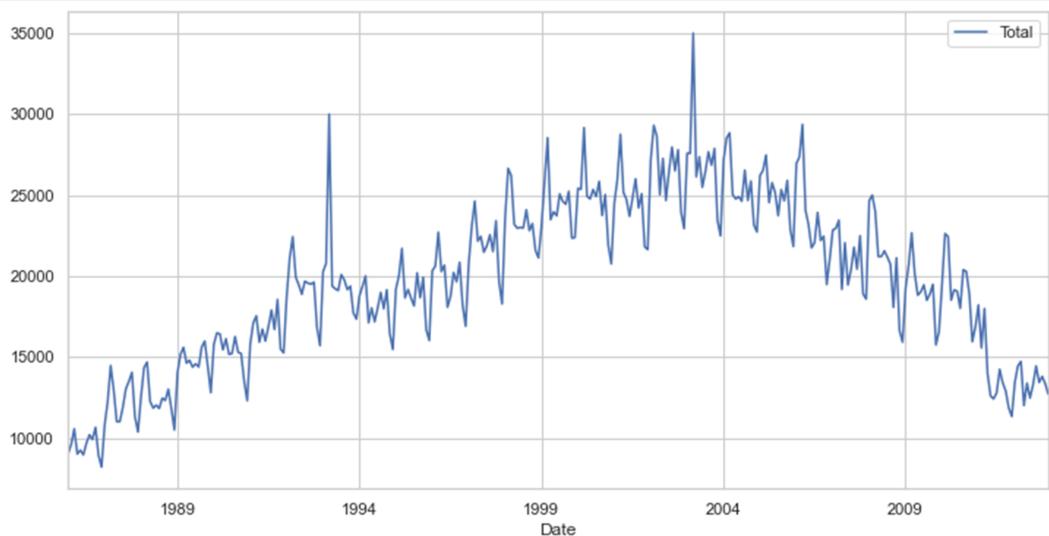
GPT-4V

The image displays a scatter plot with points following a roughly upward curving trend. Most of the points are closely aligned with this trend, but there is one point located near the (2, 40) mark that deviates from the general pattern. This point can be considered an anomaly or outlier because it does not fit the general trend observed in the rest of the data points.

Figure 36 | Time Series Anomaly Detection: Case 1, from Outlier Detection Dataset [89]. Green highlights the expected information outputted by GPT-4V.

Time-series Anomaly Detection: Case2

Image Prompt



Language Prompt

Please determine whether the image contains anomalies or outlier points. If yes, give a specific reason.

GPT-4V

The image you provided is a time series plot spanning from 1989 to 2009. Upon analyzing the graph: There is a **prominent peak around the year 1994**. This is an anomaly as it significantly deviates from the surrounding data points. Another **notable peak is observed around the year 2004**. This also stands out as **an anomaly compared to its neighboring data points**. These peaks can be considered outlier points because they represent a **sharp increase that is not in line with the general trend observed in the surrounding years**. Such deviations might be indicative of certain events or changes that occurred during those years.

Figure 37 | Time Series Anomaly Detection: Case 2, from Catfish Sales Dataset [2]. Green highlights the expected information outputted by GPT-4V.

References

- [1] Amit Adam, Ehud Rivlin, Ilan Shimshoni, and Daviv Reinitz. Robust real-time unusual event detection using multiple fixed-location monitors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(3):555–560, 2008.
- [2] Neptune AI. Anomaly detection in time series. <https://neptune.ai/blog/anomaly-detection-in-time-series>, 2023. Accessed: 2023-11-04.
- [3] Samet Akçay, Amir Atapour-Abarghouei, and T. Breckon. Gandomaly: Semi-supervised anomaly detection via adversarial training. In *Asian Conference on Computer Vision*, 2018.
- [4] Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. Palm 2 technical report. *arXiv preprint arXiv:2305.10403*, 2023.
- [5] Kilian Batzner, Lars Heckler, and Rebecca König. Efficientad: Accurate visual anomaly detection at millisecond-level latencies. *arXiv preprint arXiv:2303.14535*, 2023.
- [6] Paul Bergmann, Kilian Batzner, Michael Fauser, David Sattlegger, and Carsten Steger. The MVTec anomaly detection dataset: A comprehensive real-world dataset for unsupervised anomaly detection. *International Journal of Computer Vision*, 129(4):1038–1059, 2021.
- [7] Paul Bergmann, Kilian Batzner, Michael Fauser, David Sattlegger, and Carsten Steger. Beyond dents and scratches: Logical constraints in unsupervised anomaly detection and localization. *International Journal of Computer Vision*, 130(4):947–969, 2022.
- [8] Paul Bergmann, Xin Jin, David Sattlegger, and Carsten Steger. The MVTec 3d-AD dataset for unsupervised 3d anomaly detection and localization. In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, pages 202–213, 2022.
- [9] Paul Bergmann and David Sattlegger. Anomaly detection in 3d point clouds using deep geometric descriptors. *arXiv preprint arXiv:2202.11660*, 2022.
- [10] Ane Bl'azquez-Garc'ia, Angel Conde, Usue Mori, and José Antonio Lozano. A review on outlier/anomaly detection in time series data. *ACM Computing Surveys*, 54:1 – 33, 2020.
- [11] Hanna Borgli, Vajira Thambawita, Pia H Smedsrud, Steven Hicks, Debesh Jha, Sigrun L Eskeland, Kristin Ranheim Randel, Konstantin Pogorelov, Mathias Lux, Duc Tien Dang Nguyen, et al. Hyperkvasir, a comprehensive multi-class image and video dataset for gastrointestinal endoscopy. *Scientific data*, 7(1):283, 2020.
- [12] Yuxuan Cai, Dingkang Liang, Dongliang Luo, Xinwei He, Xin Yang, and Xiang Bai. A discrepancy aware framework for robust anomaly detection. *IEEE Transactions on Industrial Informatics*, pages 1–10, 2023.
- [13] Yunkang Cao, Yanan Song, Xiaohao Xu, Shuya Li, Yuhao Yu, Yifeng Zhang, and Weiming Shen. Semi-supervised knowledge distillation for tiny defect detection. In *2022 IEEE 25th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 1010–1015. IEEE, 2022.
- [14] Yunkang Cao, Qian Wan, Weiming Shen, and Liang Gao. Informative knowledge distillation for image anomaly segmentation. *Knowledge-Based Systems*, 248:108846, 2022.
- [15] Yunkang Cao, Xiaohao Xu, Zhaoge Liu, and Weiming Shen. Collaborative discrepancy optimization for reliable image anomaly localization. *IEEE Transactions on Industrial Informatics*, pages 1–10, 2023.
- [16] Yunkang Cao, Xiaohao Xu, and Weiming Shen. Complementary pseudo multimodal feature for point cloud anomaly detection. *arXiv preprint arXiv:2303.13194*, 2023.
- [17] Yunkang Cao, Xiaohao Xu, Chen Sun, Yuqi Cheng, Zongwei Du, Liang Gao, and Weiming Shen. Segment any anomaly without training via hybrid prompt regularization. *arXiv preprint arXiv:2305.10724*, 2023.
- [18] Navoneel Chakrabarty. Brain mri images for brain tumor detection, 2019.
- [19] Raghavendra Chalapathy and Sanjay Chawla. Deep learning for anomaly detection: A survey. *arXiv preprint arXiv:1901.03407*, 2019.

- [20] Varun Chandola, Arindam Banerjee, and Vipin Kumar. Anomaly detection: A survey. *ACM Computing Surveys*, 41(3), jul 2009.
- [21] Rui Chen, Guoyang Xie, Jiaqi Liu, Jinbao Wang, Ziqi Luo, Jinfan Wang, and Feng Zheng. Easynet: An easy network for 3d industrial anomaly detection. *Proceedings of the 31st ACM International Conference on Multimedia*, 2023.
- [22] Xuhai Chen, Yue Han, and Jiangning Zhang. A zero-/few-shot anomaly classification and segmentation method for CVPR 2023 VAND workshop challenge tracks 1&2: 1st place on zero-shot AD and 4th place on few-shot AD. *arXiv preprint arXiv:2305.17382*, 2023.
- [23] Xiaoran Chen, Suhang You, Kerem Can Tezcan, and Ender Konukoglu. Unsupervised lesion detection via image restoration with a normative prior. *Medical image analysis*, 64:101713, 2020.
- [24] Yong Shean Chong and Yong Haur Tay. Abnormal event detection in videos using spatiotemporal autoencoder. In *International symposium on neural networks*, pages 189–196. Springer, 2017.
- [25] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*, 2022.
- [26] Noel CF Codella, David Gutman, M Emre Celebi, Brian Helba, Michael A Marchetti, Stephen W Dusza, Aadi Kalloo, Konstantinos Liopyris, Nabin Mishra, Harald Kittler, et al. Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). In *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)*, pages 168–172. IEEE, 2018.
- [27] Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale Fung, and Steven Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning. *arXiv preprint arXiv:2305.06500*, 2023.
- [28] Thomas Defard, Aleksandr Setkov, Angelique Loesch, and Romaric Audigier. Padim: a patch distribution modeling framework for anomaly detection and localization. In *International Conference on Pattern Recognition*, pages 475–489. Springer, 2021.
- [29] Jan Diers and Christian Pigorsch. A survey of methods for automated quality control based on images. *International Journal of Computer Vision*, 2023.
- [30] Min Du, Feifei Li, Guineng Zheng, and Vivek Srikanth. Deeplog: Anomaly detection and diagnosis from system logs through deep learning. In *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, 2017.
- [31] Tharindu Fernando, Harshala Gammulle, Simon Denman, Sridha Sridharan, and Clinton Fookes. Deep learning for medical anomaly detection—a survey. *ACM Computing Surveys (CSUR)*, 54(7):1–37, 2021.
- [32] Alberto Floris, Luca Frittoli, Diego Carrera, and Giacomo Boracchi. Composite layers for deep anomaly detection on 3d point clouds. *arXiv preprint arXiv:2209.11796*, 2022.
- [33] Harrou Fouzi and Ying Sun. Enhanced anomaly detection via pls regression models and information entropy theory. In *IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 383–388, 2015.
- [34] Jingkun Gao, Xiaomin Song, Qingsong Wen, Pichao Wang, Liang Sun, and Huan Xu. Robusttad: Robust time series anomaly detection via decomposition and convolutional neural networks. *arXiv preprint arXiv:2002.09545*, 2020.
- [35] Dong Gong, Lingqiao Liu, Vuong Le, Budhaditya Saha, Moussa Reda Mansour, Svetha Venkatesh, and Anton van den Hengel. Memorizing normality to detect anomaly: Memory-augmented deep autoencoder for unsupervised anomaly detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1705–1714, 2019.
- [36] Tao Gong, Chengqi Lyu, Shilong Zhang, Yudong Wang, Miao Zheng, Qian Zhao, Kuikun Liu, Wenwei Zhang, Ping Luo, and Kai Chen. Multimodal-gpt: A vision and language model for dialogue with humans, 2023.
- [37] Zhaopeng Gu, Bingke Zhu, Guibo Zhu, Yingying Chen, Ming Tang, and Jinqiao Wang. Anomalygpt: Detecting industrial anomalies using large vision-language models. *arXiv preprint arXiv:2308.15366*, 2023.

- [38] Mahmudul Hasan, Jonghyun Choi, Jan Neumann, Amit K Roy-Chowdhury, and Larry S Davis. Learning temporal regularity in video sequences. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 733–742, 2016.
- [39] Lars Heckler, Rebecca König, and Paul Bergmann. Exploring the importance of pretrained feature extractors for unsupervised anomaly detection and localization. In *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 2917–2926, 2023.
- [40] Chaoqin Huang, Haoyan Guan, Aofan Jiang, Ya Zhang, Michael Spratling, and Yan-Feng Wang. Registration based few-shot anomaly detection. In *European Conference on Computer Vision*, pages 303–319. Springer, 2022.
- [41] Chao Huang, Chengliang Liu, Jie Wen, Lian Wu, Yong Xu, Qiuping Jiang, and Yaowei Wang. Weakly supervised video anomaly detection via self-guided temporal discriminative transformer. *IEEE Transactions on Cybernetics*, pages 1–14, 2022.
- [42] Chao Huang, Jie Wen, Yong Xu, Qiuping Jiang, Jian Yang, Yaowei Wang, and David Zhang. Self-supervised attentive generative adversarial networks for video anomaly detection. *IEEE Transactions on Neural Networks and Learning Systems*, pages 1–15, 2022.
- [43] Chao Huang, Zehua Yang, Jie Wen, Yong Xu, Qiuping Jiang, Jian Yang, and Yaowei Wang. Self-supervision-augmented deep autoencoder for unsupervised visual anomaly detection. *IEEE Transactions on Cybernetics*, 52(12):13834–13847, 2022-12.
- [44] Tsuyoshi Idé, Ankush Khandelwal, and Jayant Kalagnanam. Sparse gaussian markov random field mixtures for anomaly detection. In *IEEE 16th International Conference on Data Mining (ICDM)*, pages 955–960, 2016.
- [45] Jongheon Jeong, Yang Zou, Taewan Kim, Dongqing Zhang, Avinash Ravichandran, and Onkar Dabeer. Winclip: Zero-/few-shot anomaly classification and segmentation. *arXiv preprint arXiv:2303.14814*, 2023.
- [46] Yuxin Jiang, Yunkang Cao, and Weiming Shen. A masked reverse knowledge distillation method incorporating global and local information for image anomaly detection. *Knowledge-Based Systems*, 280:110982, 2023.
- [47] Yang Jiao, Kai Yang, Dongjing Song, and Dacheng Tao. Timeautoad: Autonomous anomaly detection with self-supervised contrastive loss for multivariate time series. *IEEE Transactions on Network Science and Engineering*, 9(3):1604–1619, 2022.
- [48] C. Kay. Accident detection from cctv footage. <https://www.kaggle.com/datasets/ckay16/accident-detection-from-cctv-footage>, 2022. Kaggle dataset.
- [49] Daniel S Kermany, Michael Goldbaum, Wenjia Cai, Carolina CS Valentim, Huiying Liang, Sally L Baxter, Alex McKeown, Ge Yang, Xiaokang Wu, Fangbing Yan, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. *cell*, 172(5):1122–1131, 2018.
- [50] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollar, and Ross Girshick. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 4015–4026, October 2023.
- [51] Felipe Campos Kitamura. Head ct - hemorrhage, 2018.
- [52] Chunyuan Li, Zhe Gan, Zhengyuan Yang, Jianwei Yang, Linjie Li, Lijuan Wang, and Jianfeng Gao. Multimodal foundation models: From specialists to general-purpose assistants. *arXiv preprint arXiv:2309.10020*, 2023.
- [53] Chun-Liang Li, Kihyuk Sohn, Jinsung Yoon, and Tomas Pfister. Cutpaste: Self-supervised learning for anomaly detection and localization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9664–9674, 2021.
- [54] Yufei Liang, Jiangning Zhang, Shiwei Zhao, Runze Wu, Yong Liu, and Shuwen Pan. Omni-frequency channel-selection representations for unsupervised anomaly detection. *arXiv preprint arXiv:2203.00259*, 2022.

- [55] Fuxiao Liu, Tianrui Guan, Zongxia Li, Lichang Chen, Yaser Yacoob, Dinesh Manocha, and Tianyi Zhou. Hallusionbench: You see what you think? or you think what you see? an image-context reasoning benchmark challenging for gpt-4v (ision), llava-1.5, and other multi-modality models. *arXiv preprint arXiv:2310.14566*, 2023.
- [56] Fuxiao Liu, Kevin Lin, Linjie Li, Jianfeng Wang, Yaser Yacoob, and Lijuan Wang. Aligning large multi-modal model with robust instruction tuning. *arXiv preprint arXiv:2306.14565*, 2023.
- [57] Fuxiao Liu, Yaser Yacoob, and Abhinav Shrivastava. Covid-vts: Fact extraction and verification on short video platforms. *arXiv preprint arXiv:2302.07919*, 2023.
- [58] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *arXiv preprint arXiv:2304.08485*, 2023.
- [59] Jiaqi Liu, Guoyang Xie, Rui Chen, Xinpeng Li, Jinbao Wang, Yong Liu, Chengjie Wang, and Feng Zheng. Real3d-ad: A dataset of point cloud anomaly detection. *arXiv preprint arXiv:2309.13226*, 2023.
- [60] Mingxuan Liu, Yunrui Jiao, and Hong Chen. Skip-st: Anomaly detection for medical images using student-teacher network with skip connections. In *2023 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1–5, 2023.
- [61] Mingxuan Liu, Yunrui Jiao, Hongyu Gu, Jingqiao Lu, and Hong Chen. Data augmentation using image-to-image translation for tongue coating thickness classification with imbalanced data. In *2022 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, pages 90–94, 2022.
- [62] Mingxuan Liu, Yunrui Jiao, Jingqiao Lu, and Hong Chen. Anomaly detection for medical images using teacher-student model with skip connections and multi-scale anomaly consistency. *TechRxiv*, 2023.
- [63] Tongkun Liu, Bing Li, Xiao Du, Bingke Jiang, Xiao Jin, Liuyi Jin, and Zhu Zhao. Component-aware anomaly detection framework for adjustable and logical industrial visual inspection. *arXiv preprint arXiv:2305.08509*, 2023.
- [64] Cewu Lu, Jianping Shi, and Jiaya Jia. Abnormal event detection at 150 fps in matlab. In *IEEE International Conference on Computer Vision*, pages 2720–2727, 2013.
- [65] Ruiying Lu, YuJie Wu, Long Tian, Dongsheng Wang, Bo Chen, Xiyang Liu, and Ruimin Hu. Hierarchical vector quantized transformer for multi-class unsupervised anomaly detection. *arXiv preprint arXiv:2310.14228*, 2023.
- [66] Weixin Luo, Wen Liu, and Shenghua Gao. Remembering history with convolutional lstm for anomaly detection. In *IEEE International Conference on Multimedia and Expo (ICME)*, pages 439–444, 2017.
- [67] Weixin Luo, Wen Liu, and Shenghua Gao. Remembering history with convolutional lstm for anomaly detection. In *2017 IEEE International conference on multimedia and expo (ICME)*, pages 439–444. IEEE, 2017.
- [68] Weixin Luo, Wen Liu, and Shenghua Gao. A revisit of sparse coding based anomaly detection in stacked rnn framework. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 341–349, 2017.
- [69] Vijay Mahadevan, Weixin Li, Viral Bhalodia, and Nuno Vasconcelos. Anomaly detection in crowded scenes. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1975–1981, 2010.
- [70] Jefferson Ryan Medel and Andreas Savakis. Anomaly detection in video using predictive convolutional long short-term memory networks. *arXiv preprint arXiv:1612.00390*, 2016.
- [71] OpenAI. Gpt-4v(ision) system card. 2023.
- [72] Guansong Pang, Chunhua Shen, Longbing Cao, and Anton van den Hengel. Deep learning for anomaly detection. *ACM Computing Surveys*, 54:1 – 38, 2020.
- [73] Hyunjong Park, Jongyoun Noh, and Bumsub Ham. Learning memory-guided normality for anomaly detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14372–14381, 2020.
- [74] Mahdyar Ravanbakhsh, Moin Nabi, Enver Sangineto, Lucio Marcenaro, Carlo Regazzoni, and Nicu Sebe. Abnormal event detection in videos using generative adversarial nets. In *IEEE International Conference on Image Processing (ICIP)*, pages 1577–1581, 2017.

- [75] Tal Reiss, Niv Cohen, Liron Bergman, and Yedid Hoshen. Panda: Adapting pretrained features for anomaly detection and segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2806–2814, 2021.
- [76] Karsten Roth, Latha Pemula, Joaquin Zepeda, Bernhard Schölkopf, Thomas Brox, and Peter Gehler. Towards total recall in industrial anomaly detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14318–14328, 2022.
- [77] Marco Rudolph, Tom Wehrbein, Bodo Rosenhahn, and Bastian Wandt. Asymmetric student-teacher networks for industrial anomaly detection. In *2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 2591–2601, 2022.
- [78] Lukas Ruff, Jacob R. Kauffmann, Robert A. Vandermeulen, Gregoire Montavon, Wojciech Samek, Marius Kloft, Thomas G. Dietterich, and Klaus-Robert Muller. A unifying review of deep and shallow anomaly detection. *Proceedings of the IEEE*, 109(5):756–795, 2021.
- [79] Mayu Sakurada and Takehisa Yairi. Anomaly detection using autoencoders with nonlinear dimensionality reduction. In *Proceedings of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis*, MLSDA’14, page 4–11, New York, NY, USA, 2014. Association for Computing Machinery.
- [80] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *Advances in Neural Information Processing Systems*, 35:25278–25294, 2022.
- [81] Aleksandar Shtedritski, Christian Rupprecht, and Andrea Vedaldi. What does clip know about a red circle? visual prompt engineering for vlms. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 11987–11997, October 2023.
- [82] Kihyuk Sohn, Chun-Liang Li, Jinsung Yoon, Minho Jin, and Tomas Pfister. Learning and evaluating representations for deep one-class classification. In *International Conference on Learning Representations*, 2020.
- [83] Ya Su, Youjian Zhao, Chenhao Niu, Rong Liu, Wei Sun, and Dan Pei. Robust anomaly detection for multivariate time series through stochastic recurrent neural network. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, pages 2828–2837, 2019.
- [84] Waqas Sultani, Chen Chen, and Mubarak Shah. Real-world anomaly detection in surveillance videos. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2018.
- [85] Waqas Sultani, Chen Chen, and Mubarak Shah. Real-world anomaly detection in surveillance videos. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 6479–6488, 2018.
- [86] Hanlin Tan, Yongping Zhai, Yu Liu, and Maojun Zhang. Fast anomaly detection in traffic surveillance video based on robust sparse optical flow. In *IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 1976–1980, 2016.
- [87] Yu Tian, Fengbei Liu, Guansong Pang, Yuanhong Chen, Yuyuan Liu, Johan W Verjans, Rajvinder Singh, and Gustavo Carneiro. Self-supervised pseudo multi-class pre-training for unsupervised anomaly detection and segmentation in medical images. *Medical Image Analysis*, 90:102930, 2023.
- [88] Yu Tian, Guansong Pang, Fengbei Liu, Yuanhong Chen, Seon Ho Shin, Johan W Verjans, Rajvinder Singh, and Gustavo Carneiro. Constrained contrastive distribution learning for unsupervised anomaly detection and localisation in medical images. In *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part V 24*, pages 128–140. Springer, 2021.
- [89] Stack Exchange User. Simple outlier detection for time series. <https://stats.stackexchange.com/questions/427327/simple-outlier-detection-for-time-series>, 2021. Accessed: 2023-11-04.
- [90] Shashanka Venkataramanan, Kuan-Chuan Peng, Rajat Vikram Singh, and Abhijit Mahalanobis. Attention guided anomaly localization in images. In *European Conference on Computer Vision*, pages 485–503. Springer, 2020.
- [91] Qian Wan, Yunkang Cao, Liang Gao, Weiming Shen, and Xinyu Li. Position encoding enhanced feature mapping for image anomaly detection. In *2022 IEEE 18th International Conference on Automation Science and Engineering (CASE)*, pages 876–881. IEEE, 2022-08-20.

- [92] Qian Wan, Liang Gao, and Xinyu Li. Logit inducing with abnormality capturing for semi-supervised image anomaly detection. *IEEE Transactions on Instrumentation and Measurement*, 71:1–12, 2022.
- [93] Qian Wan, Liang Gao, Xinyu Li, and Long Wen. Industrial image anomaly localization based on gaussian clustering of pretrained feature. *IEEE Transactions on Industrial Electronics*, 69(6):6182–6192.
- [94] Qian Wan, Liang Gao, Xinyu Li, and Long Wen. Unsupervised image anomaly detection and segmentation based on pretrained feature mapping. 19(3):2330–2339, 2023-03.
- [95] Guodong Wang, Shumin Han, Errui Ding, and Di Huang. Student-teacher feature pyramid matching for anomaly detection. In *British Machine Vision Conference*, 2021.
- [96] Yue Wang, Jinlong Peng, Jiangning Zhang, Ran Yi, Yabiao Wang, and Chengjie Wang. Multimodal industrial anomaly detection via hybrid fusion. *arXiv preprint arXiv:2303.00601*, 2023.
- [97] Chaoyi Wu, Jiayu Lei, Qiaoyu Zheng, Weike Zhao, Weixiong Lin, Xiaoman Zhang, Xiao Zhou, Ziheng Zhao, Ya Zhang, Yanfeng Wang, and Weidi Xie. Can GPT-4v(ision) serve medical applications? case studies on GPT-4v for multimodal medical diagnosis. *arXiv preprint arXiv:2310.09909*, 2023.
- [98] Guoyang Xie, Jingbao Wang, Jiaqi Liu, Jiayi Lyu, Yong Liu, Chengjie Wang, Feng Zheng, and Yaochu Jin. IM-IAD: Industrial image anomaly detection benchmark in manufacturing. *arXiv preprint arXiv:2301.13359*, 2023.
- [99] Guoyang Xie, Jingbao Wang, Jiaqi Liu, Feng Zheng, and Yaochu Jin. Pushing the limits of fewshot anomaly detection in industry vision: Graphcore. In *International Conference on Learning Representations*, 2023.
- [100] Jianwei Yang, Hao Zhang, Feng Li, Xueyan Zou, Chunyuan Li, and Jianfeng Gao. Set-of-mark prompting unleashes extraordinary visual grounding in GPT-4v. *arXiv preprint, arXiv:2310.11441*, 2023.
- [101] Zhengyuan Yang, Linjie Li, Kevin Lin, Jianfeng Wang, Chung-Ching Lin, Zicheng Liu, and Lijuan Wang. The dawn of lmms: Preliminary explorations with gpt-4v (ision). *arXiv preprint arXiv:2309.17421*, 2023.
- [102] Haiming Yao, Wei Luo, Wenyong Yu, Xiaotian Zhang, Zhenfeng Qiang, Donghao Luo, and Hui Shi. Dual-attention transformer and discriminative flow for industrial visual anomaly detection. *IEEE Transactions on Automation Science and Engineering*, pages 1–15, 2023.
- [103] Haiming Yao, Wenyong Yu, Wei Luo, Zhenfeng Qiang, Donghao Luo, and Xiaotian Zhang. Learning global-local correspondence with semantic bottleneck for logical anomaly detection. *IEEE Transactions on Circuits and Systems for Video Technology*, pages 1–1, 2023.
- [104] Mingze Yuan, Yingda Xia, Hexin Dong, Zifan Chen, Jiawen Yao, Mingyan Qiu, Ke Yan, Xiaoli Yin, Yu Shi, Xin Chen, et al. Devil is in the queries: Advancing mask transformers for real-world medical image segmentation and out-of-distribution localization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 23879–23889, 2023.
- [105] Andrei Zaharescu and Richard Wildes. Anomalous behaviour detection using spatiotemporal oriented energies, subset inclusion histogram comparison and event-driven processing. In *European Conference on Computer Vision*, pages 563–576. Springer, 2010.
- [106] J. Zhang, Masanori Suganuma, and Takayuki Okatani. Contextual affinity distillation for image anomaly detection. *arXiv preprint arXiv:2307.03101*, 2023.
- [107] Jianpeng Zhang, Yutong Xie, Yi Li, Chunhua Shen, and Yong Xia. Covid-19 screening on chest x-ray images using deep learning based anomaly detection. *arXiv preprint arXiv:2003.12338*, 2020.
- [108] Yuxin Zhang, Jindong Wang, Yiqiang Chen, Han Yu, and Tao Qin. Adaptive memory networks with self-supervised learning for unsupervised anomaly detection. *IEEE Transactions on Knowledge and Data Engineering*, 2022.
- [109] Bin Zhao, Li Fei-Fei, and Eric P. Xing. Online detection of unusual events in videos via dynamic sparse coding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3313–3320, 2011.
- [110] Hang Zhao, Yujing Wang, Juanyong Duan, Congrui Huang, Defu Cao, Yunhai Tong, Bixiong Xu, Jing Bai, Jie Tong, and Qi Zhang. Multivariate time-series anomaly detection via graph attention network. In *2020 IEEE International Conference on Data Mining (ICDM)*, pages 841–850. IEEE, 2020.

- [111] Qiang Zhou, Weize Li, Lihang Jiang, Guoliang Wang, Guyue Zhou, Shanghang Zhang, and Hao Zhao. Pad: A dataset and benchmark for pose-agnostic anomaly detection. *arXiv preprint arXiv:2310.07716*, 2023.
- [112] Qihang Zhou, Guansong Pang, Yu Tian, Shibo He, and Jiming Chen. Anomalyclip: Object-agnostic prompt learning for zero-shot anomaly detection. *arXiv preprint arXiv:2310.18961*, 2023.
- [113] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.
- [114] David Zimmerer, Peter M. Full, Fabian Isensee, Paul Jäger, Tim Adler, Jens Petersen, Gregor Köhler, Tobias Ross, Annika Reinke, Antanas Kascenas, Bjørn Sand Jensen, Alison Q. O’Neil, Jeremy Tan, Benjamin Hou, James Batten, Huaqi Qiu, Bernhard Kainz, Nina Shvetsova, Irina Fedulova, Dmitry V. Dylov, Baolun Yu, Jianyang Zhai, Jingtao Hu, Runxuan Si, Sihang Zhou, Siqi Wang, Xinyang Li, Xuerun Chen, Yang Zhao, Sergio Naval Marimont, Giacomo Tarroni, Victor Saase, Lena Maier-Hein, and Klaus Maier-Hein. Mood 2020: A public benchmark for out-of-distribution detection and localization on medical images. *IEEE Transactions on Medical Imaging*, 41(10):2728–2738, 2022.
- [115] Bo Zong, Qi Song, Martin Renqiang Min, Wei Cheng, Cristian Lumezanu, Daeki Cho, and Haifeng Chen. Deep autoencoding gaussian mixture model for unsupervised anomaly detection. In *International conference on learning representations*, 2018.
- [116] Yang Zou, Jongheon Jeong, Latha Pemula, Dongqing Zhang, and Onkar Dabeer. Spot-the-difference self-supervised pre-training for anomaly detection and segmentation. In *European Conference on Computer Vision*, pages 392–408. Springer, 2022.