Camera as a Sensor Towards Augmenting Anomaly Detection in the Internet of Things Systems: A Survey

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Camera sensors play an essential role in Internet of Things (IoT) devices and have revolutionized surveillance tasks by replacing human supervision with computer vision. A challenging and essential task in automated video surveillance is accurately detecting anomalous observations. An anomaly is an abnormal data pattern that deviates from the *normal*, i.e., frequently occurring, pattern. This survey presents a comprehensive review of sensor-based anomaly detection systems focusing on cameras. We first provide definitions of the fundamental concepts in anomaly detection and the use of sensors in this context. We categorize and analyze anomaly detection using vision (i.e., camera) and non-vision sensors. We also investigate the adoption of camera sensors in different applications, describe hybrid anomaly detection techniques, and identify potential opportunities. Open research challenges and use cases that demonstrate unaddressed camera-based anomaly detection are used to motivate future work in this area.

CCS Concepts: • **Computer systems organization** → **Sensor networks**; • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: Anomaly Detection, Camera systems, Cyber-physical systems

1 INTRODUCTION

The significant expansion in Wireless Sensor Networks (WSN) and IoT has enabled the monitoring and recording of daily activities and operations. Billions of sensors and actuators are utilized in multiple environments. These sensors produce a wealth of heterogeneous data of different types, such as binary, discrete, continuous, audio, and video. Extracting useful information from a large amount of data requires multiple tasks. One fundamental task is to learn the normal behavior and detect abnormal patterns, i.e., anomalies [144].

An *anomaly* refers to measurements or data that deviate from the expected or normal pattern. *Anomaly detection* is the problem of finding these deviations. An anomaly is also referred to as abnormal, outlier, and discordant observations [28]. This article will use anomalies, abnormalities, or outliers in the following sections. An anomaly can occur for different reasons, such as human violations of rules, system failure, machine errors, and fraudulent actions. Additionally, anomalies can occur in spatial and temporal contexts [28].

Detecting abnormalities in sensor systems, an essential component of IoT systems has drawn the attention of many academics. Anomaly detection in IoT is vital because anomalous data primarily reflects critical actionable information. Thus, anomaly detection systems have been deployed in multiple sectors. For example, in road traffic, anomalies such as illegal U-turns, car accidents, and pedestrians walking in unexpected areas of the road have been observed and detected [111]. On the other hand, anomaly detection is used in healthcare to analyze medical records where MRI images can reveal the presence of a tumor, or abnormal ECG traces can indicate cardiac issues [126]. Additionally, events such as falling, intrusion, sleep disruption, and confusion can raise alarms for anomalous behavior in smart homes [10, 49].

Anomaly detection is a crucial problem that has gained attention in multiple research and industry domains. Several general techniques have been developed for anomaly detection, while

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others are specific to application fields. This survey investigates 50 anomaly detection research using sensors in the past decade. We classify sensors as vision (i.e., camera) and non-vision and analyze applications in each category. Non-vision sensors include temperature, motion, humidity, pressure, light, and magnetic field. Additionally, we focus on the role of the camera in identifying outliers and recognizing its capabilities to augment non-vision-based anomaly detection.

In recent years, the adoption and investigation of cameras have continuously grown in public, industry, and academia, extending into homes [50]. As the urban population has rapidly increased, cameras have enhanced people's management and surveillance tasks in public and private places [36]. They have been used in roads, critical infrastructures, banks, elder-care centers, and homes [18, 21, 49, 91, 111] to provide functionalities such as people counting, aiding visually impaired individuals in shopping, detecting road damage, and recognizing aggressive human activities. Anomaly detection is a primary task in surveillance systems. In our survey, we investigate anomaly detection using vision and non-vision sensors to explore the effect and opportunities of integrating these sensors towards detecting anomalies in hybrid systems. Figure 1 depicts the context of our review and examples of sensors used for anomaly detection.

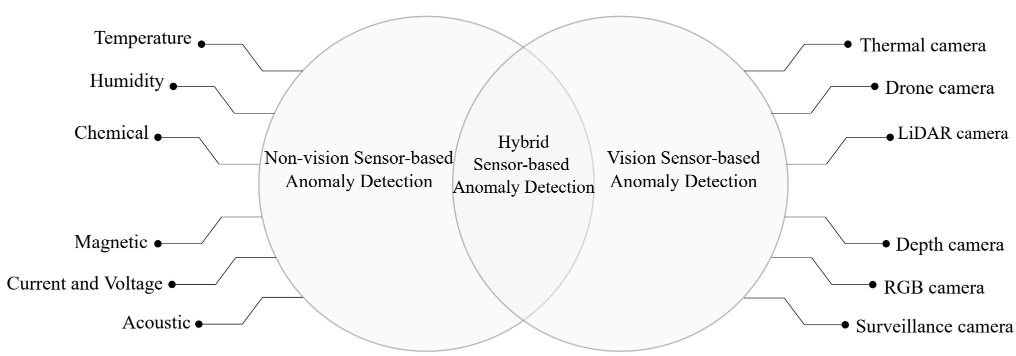

Fig. 1. Related concepts: Non-vision-based anomaly detection (which uses sensors such as temperature, humidity, sound, and others.), Vision-based anomaly detection (which uses sensors such as RGB and depth cameras), and the integration of the two applications in hybrid sensor-based anomaly detection.

1.1 Existing Surveys

Anomaly detection has been investigated in various survey and reviews articles and analyzed using different classification criteria. It has been studied since 1887; Edgeworth [42] provided the first definition of *discordant observation.*

The analysis of related surveys presented below is divided into three parts. First, we highlight surveys investigating anomaly detection using non-vision sensors. Second, we introduce review articles on vision-based anomaly detection. Third, we present surveys on camera systems. The works are introduced in chronological order.

A broad review of six categories of anomaly detection techniques and seven application domains was given in [28]. They briefly outlined sensor networks as an application domain. In a 2010 survey, Zhang et al. surveyed outlier detection techniques specifically developed for WSN, where they identified four factors to compare outlier detection techniques [144]. Similarly, Oreilly et al. [99] reviewed anomaly detection in WSN in a non-stationary environment where normal data can evolve and require updating the trained model. Unfortunately, neither of the works is interested in exploring the roles of various sensors for anomaly detection, which is our focus.

Table 1. Summary of Existing Surveys on Anomaly Detection and Camera Systems. In Contrast to Our Work, Existing Surveys Mainly Focus on Specific Areas of Sensor-based Anomaly Detection and Camera Systems.

Reference	Non-vision Anomaly Detection	Vision Anomaly Detection	Camera Systems
Chandola et al. [28]	*		
Oreilly et al. [99]	*		
Fahim and Sillitti [43]	*		
Cook et al. [38]	*		
Popoola and Wang [104]		*	
Santhosh et al. [111]		*	
Nayak et al. [95]		*	
Natarajan et al. [93]		*	
Liu et al. [80]			*
Antunes et al. [9]			*
Olagoke et al. [98]			*
Our work	*	*	*

With the rise of IoT, an interesting body of surveys has been published discussing the problem of anomaly detection. In 2019, anomaly detection techniques from the perspective of statistics and machine learning in an IoT environment were reviewed in [43]. In addition, anomaly detection in time-series data for IoT was surveyed in [38].

Several surveys have investigated anomaly detection in visual data. A focused review of abnormal human behavior in video surveillance was presented in [104]. Anomalous road traffic scenarios were reviewed in [111]. Deep learning anomaly detection methods were surveyed in [95]. While their emphasis is on visual outliers, we focus on both vision and non-vision anomalies.

Regarding camera systems, Natarajan et al. [93] published a comprehensive review of multi-camera coordination and control for surveillance applications over two decades. The camera placement problem in large surveillance areas was reviewed in [80]. Antunes et al. [9] summarized state-of-the-art sensor technologies to monitor the workflow of healthcare environments with a focus on real-time location systems and computer vision. Another review paper by Olagoke et al. [98] discussed multi-camera systems' physical formation, calibration architectures, and algorithms. Table 1 provides a summary of existing surveys and reviews that compare and analyze anomaly detection techniques based on different classification criteria in the field of anomaly detection, including non-vision sensors, vision-based anomaly detection, and camera systems.

Our survey differs from previous works in several ways. We explore the intersection between anomaly detection using non-vision sensors and anomaly detection using cameras. We extensively review sensor-based anomaly detection systems and classify sensing technologies into vision-based and non-vision-based. We then analyze and identify detected anomalies using each sensor in various physical spaces.

1.2 Contribution

This survey aims to provide a detailed review and analysis of sensor-based anomaly detection systems, specifically using camera sensors. The main contributions of this survey are as follows:

- Provide a comprehensive review of the state-of-the-art research in anomaly detection using sensors, with a focus on camera sensors for anomaly detection.
- Survey the role and capabilities of camera sensors in anomaly detection and computer vision. Additionally, we present an analysis of the hierarchy and approaches of computer vision systems.
- Explore the effects and opportunities of integrating vision and non-vision sensors for detecting anomalies in hybrid systems.

- Present several anomaly test cases that researchers can use as testbeds in the field of anomaly detection. Moreover, we highlight the properties of these anomaly test cases.

The rest of the paper is structured as follows: Section 2 introduces the main concepts and definitions related to sensor-based anomaly detection. It begins by defining the types of anomalies, followed by the categorization and types of sensors. Section 3 provides a discussion of non-vision-based anomaly detection systems, including the existing limitations of these sensors. Next, Section 4 delves into anomaly detection using vision sensors in detail. A comparison of different approaches for detecting anomalies is presented in Section 5. In Section 6, an overview of computer vision systems is provided, analyzing the hierarchy and approaches of existing systems. Hybrid sensor-based anomaly detection systems are investigated in Section 7. Section 8 highlights the challenges found in the literature when implementing hybrid anomaly detection, along with multiple test cases of anomalous observations. Finally, the conclusion of our work is explained in Section 9. In each anomaly detection application, we emphasize the following aspects: (1) detected anomaly, (2) sensors used for anomaly detection, (3) anomaly type, and (4) detection technique.

2 DEFINITIONS

For the convenience of the readers, this section provides essential background information to understand the field of anomaly detection and computer vision systems in the IoT environment. We identify the main types of anomalies in Section 2.1, and the classification of anomaly detection sensors is demonstrated in Section 2.2.

2.1 Anomaly Types

An anomaly is an observation that deviates from the normal pattern. It is crucial for developers of anomaly detection applications to identify the desired type of anomaly. As illustrated in Figure 2, anomalies can be classified into three types [11, 28, 92]:

(1) *Point Anomalies*: Point anomalies occur when a single data instance deviates from the rest of the data. They are the simplest form of anomalies, and much of the literature focuses on them. For example, in the case of building temperature, which generally exhibits consistent behavior, a sudden increase can be considered a point anomaly [43]. Figure 2(a) represents a point anomaly with a single high-temperature value.
(2) *Contextual Anomalies*: Contextual anomalies occur when a data point is abnormal in a specific context but would be considered normal in other contexts. These anomalies are also known as conditional anomalies. Data instances can be characterized by contextual attributes and behavioral attributes. For example, in a spatial dataset, location coordinates can be contextual attributes, while temperature degrees can be behavioral attributes. Time-series data are commonly used to investigate contextual anomalies. For instance, Figure 2(b) shows a contextual anomaly with the lowest recorded weather temperature in June [28].
(3) *Collective Anomalies*: Collective anomalies occur when data points collectively deviate from the entire dataset. Individually, these data points may appear normal, but their combination is considered anomalous. For instance, in an electrocardiogram (ECG) test, multiple instances of low values sustained over a long duration can indicate an abnormal phenomenon, whereas a single low value may not indicate abnormality [4]. Figure 2(c) illustrates a collective anomaly in an ECG signal.

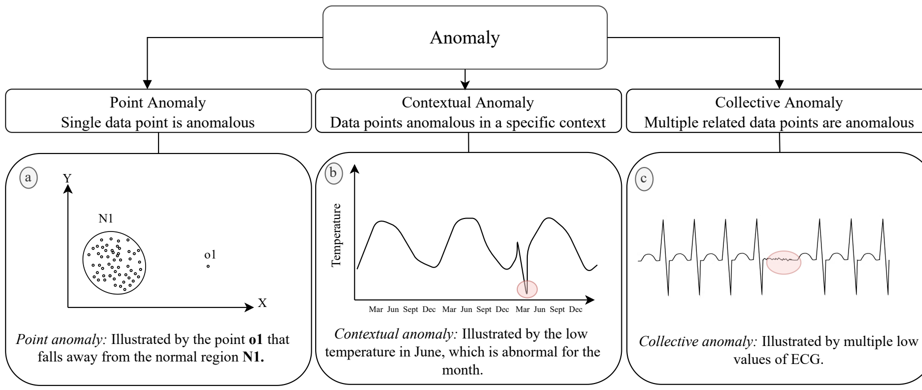

Fig. 2. Anomalies classification with an example of each anomaly type [4, 28, 43].

2.2 Sensor Categories and Types

Sensors are devices that observe physical or chemical characteristics of the environment or other objects [131]. They monitor conditions like temperature and humidity, embedded in low-cost, low-power nodes. A sensor node consists of several components, including a power unit, a processing unit (processor and memory), a communication unit, and sensors unit [125]. Due to resource constraints, sensor nodes have limited capabilities and are primarily focused on sensing physical or chemical phenomena and generating measurable data.

Sensors find applications in various domains such as healthcare, security, industry, and environmental monitoring [63]. In this survey, we specifically focus on introducing several sensors used in anomaly detection applications. Therefore, this section describes different types of sensor units commonly found in sensor nodes.

Sensors can be classified based on criteria such as application field, conversion method, sensed property, and used material [66, 112]. Figure 3 illustrates the categories and types of sensors. It is important to note that the sensor categories and types shown in Figure 3 are not exhaustive but represent the commonly used sensors in the literature for anomaly detection purposes.

In this paper, we classify sensors into two main categories:

(1) *Non-vision sensors* do not use imaging or optical techniques to measure a property.
(2) *Vision sensors* utilize imaging or optical techniques to measure a property.

Each category can be further classified into several types. Here are some examples of the types of sensors within each category:

- *Temperature sensors*: These sensors measure the temperature or heat energy of an area of interest. They can be categorized as contact sensors (e.g., thermometers) or non-contact sensors (e.g., infrared thermometers).
- *Humidity sensors*: Humidity sensors measure air moisture. They can be classified as relative humidity (RH) sensors, measuring humidity relative to temperature, or absolute humidity (AH) sensors, measuring humidity independently of temperature.
- *Chemical sensors*: These sensors detect chemical reactions and measure the concentration of specific components, such as CO and CO2 detectors.
- *Magnetic field sensors*: Magnetic field sensors measure the strength of the magnetic field at a particular location. They can be used in hall effect sensors for windows and doors.
- *Pressure sensors*: Pressure sensors measure the amount of physical force applied to an area or object of interest.

- *Motion sensors*: Motion sensors are used to detect the movement of an object within a certain range. Common types of motion sensors include Passive Infrared (PIR) sensors, ultrasonic sensors, and accelerometers.
- *Acoustic sensors*: Acoustic sensors detect sound waves in the air or other media and convert them into electrical signals. Examples of acoustic sensors include microphones.
- *Optical sensors*: Optical sensors detect electromagnetic energies like light and measure physical quantities such as light intensity. Examples include image sensors and light sensors.
- *Current and voltage sensors*: Current and voltage sensors are used to monitor the current and voltage for energy monitoring purposes.

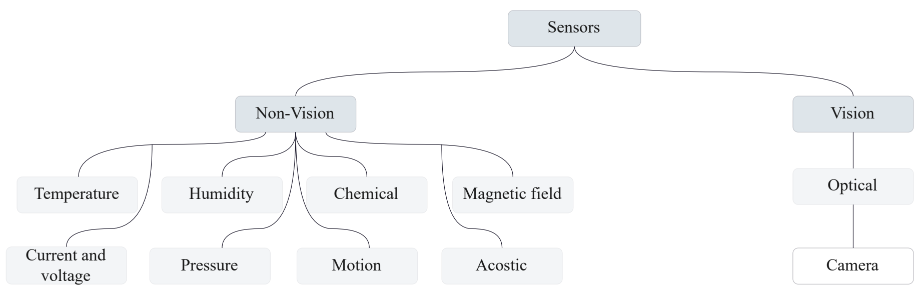

Fig. 3. Sensors Categories and Types for Anomaly Detection [66, 88, 112]

These are just some examples of sensors commonly used in anomaly detection applications. The classification provides a broad overview of the categories but is not exhaustive.

3 NON-VISION-BASED ANOMALY DETECTION

Anomaly detection techniques have been developed for various applications and domains, utilizing different approaches. These domains include intrusion and fraud detection, medical and public health, industrial damage detection, anomaly detection in text data, and sensor networks [28].

In our work, we classify spaces into three categories: outdoor, indoor, and transitional, following the method presented in [71]. The classification of spaces is based on eleven properties: access (unrestricted or gated), traversal (movement within the space), landmarks (features aiding in finding ways), line of sight (clear or limited visibility), function (activities performed in the space), enclosure, protection from elements (e.g., weather), length of stay, frequentation (number of people present in the space), dimensionality (2.5D or 3D), and ownership (private or public). It should be noted that some spaces can belong to multiple categories, such as ATMs.

In this section, our focus is on reviewing anomaly detection systems that utilize sensors to detect abnormal observations in outdoor, indoor, and transitional spaces. The goal is to introduce various applications, understand their capabilities, and identify opportunities to improve their performance. We start by presenting anomalies for each application in outdoor spaces in Section 3.1, indoor spaces in Section 3.2, and transitional spaces in Section 3.3. For each application, we identify the type of anomaly and the sensors used. A summary of existing works in non-vision-based anomaly detection is presented in Table 2 at the end of this section. Finally, in Section 3.4, we highlight the limitations of these sensors.

3.1 Outdoors Anomaly Detection using Non-vision Sensors

In the transportation field, anomaly detection using non-vision sensors has been applied to various scenarios. For instance, parking occupancy anomalies were detected using parking sensors in city parking lots [146]. Risky and aggressive driving behaviors were identified using GPS and Inertial Measurement Unit (IMU) sensors integrated into smartphones, which include accelerometer, gyroscope, and magnetometer sensors [20, 26]. GPS data has also been utilized to identify anomalies in urban traffic flow [70]. Road anomalies such as speed bumps, potholes, and obstacles have been detected using accelerometer sensors in a microcontroller board [6].

Air pollution monitoring is another area where non-vision sensors are used for anomaly detection. Anomalous data points were identified using Air Quality Index (AQI) to pinpoint unhealthy locations in a city. Simulated data of various pollutants, such as carbon monoxide, nitrogen dioxide, sulfur dioxide, particulate matter, and ozone index levels, were utilized for detection [57]. Personal air pollution monitoring systems employing gas sensors have also been developed to detect unhealthy levels of ozone (O_3) concentrations [83].

In the security and surveillance field, non-vision sensors, such as PIR and ultrasonic sensors, have been used to detect intruders in agricultural fields [110]. These sensors can capture anomalies and trigger alerts when unexpected movement is detected.

These examples demonstrate the application of non-vision sensors for anomaly detection in outdoor environments, such as transportation, air pollution monitoring, and security and surveillance.

3.2 Indoors Anomaly Detection using Non-vision Sensors

In the context of Building Energy Management Systems (BEMSs), anomalous behavior detection has been applied to minimize energy consumption. Wijayasekara et al. [132] detected anomalies such as high zone temperature, closed air supply vents, and open windows (causing inconsistencies between zone and supply air temperature) using temperature sensors to measure individual zone temperatures. Similarly, Chou and Telaga [35] identified anomalous power consumption using a smart meter equipped with various sensors, including temperature, humidity, CO_2, CO, and illumination sensors. Outliers in temperature were detected in [141] using TI CC2650 SensorTags that contained sensors for temperature, light, humidity, pressure, and magnetic field.

In the healthcare domain, research on Ambient Assisted Living (AAL) focuses on improving elderly safety. Abnormal patterns in the behavior of older adults have been analyzed in various studies [10, 39, 114, 147]. Shin et al. [114] targeted ten abnormal conditions classified into three features: activity level, mobility level, and nonresponse interval (NRI). Infrared (IR) motion sensors were used to monitor activities. Zhu et al. [147] classified anomalies in human behavior into four categories: spatial anomaly, timing anomaly, duration anomaly, and sequence anomaly. They developed a wearable body sensor network consisting of motion sensors and a Zigbee wireless receiver. Arifoglu and Bouchachia [10] investigated abnormal activities in people with dementia, such as repeating activities, sleep disruption, and confusion. Motion and door sensors were used to detect these abnormal activities. Dahmen and Cook [39] utilized motion, ambient light, door, and ambient temperature sensors to detect health-related anomalies including falls, nocturia, muscle weakness, and depression-related behavior.

Insomnia and sleep deprivation were detected using radio frequency (RF) signals reflected from the user and the bed to analyze their location, breathing, and sleeping routines in [55]. Air pollution was studied in [87], where any sharp increase in fine particulate matter ($PM_{2.5}$) was considered an anomaly. Multiple air quality monitors with optical sensors were used.

In the security and surveillance field, suspicious activities in smart homes were detected by Ramapatruni et al. [107]. They identified activities such as accessing the closet, the stove being on, the door being open, and manually turning on switches as anomalies when the user is absent from home. Smart plugs, wireless sensor tags, voice assistants, and smoke and CO sensors were used for detecting these suspicious activities.

In addition to outdoor air pollution, Maag et al. [83] also detected high indoor levels of CO_2 concentrations in smarter environments.

These examples illustrate the diverse applications of anomaly detection using non-vision sensors in various domains, including building energy management, healthcare, air pollution monitoring, and security and surveillance.

3.3 Transitional Space Anomaly Detection using Non-vision Sensors

Although most anomaly detection works are in outdoor and indoor spaces, limited research addresses transitional spaces. In the security and surveillance domain, Torkamani et al. [124] focused on detecting ATM attacks, like skimming, using a piezoelectric sensor to detect and convert vibrations caused by skimming devices into voltage signals for attack detection.

In the realm of public transportation, abnormal passenger flows in subway stations have been investigated in studies like [32] and [133]. These studies utilized smart cards from Automated Fare Collection (AFC) systems to track passenger movements. AFC systems employ various sensors such as RFID, NFC tags, vision sensors (for QR code reading), and magnetic sensors (for magnetic strip reading) to facilitate fare collection and passenger tracking.

To ensure passenger safety in public vehicles, Nandi et al. [90] proposed a system to detect physical discomfort experienced by passengers and identify potential attacks on them. They employed pressure sensors embedded in passenger seats to detect abnormal pressure patterns that may indicate an attack or distress.

In smart agriculture, greenhouse anomaly detection has been studied in [139]. The research aims to enable farmers to provide appropriate plant conditions by detecting anomalies in temperature, humidity, CO_2 levels, soil temperature, and humidity.

While the research in transitional spaces may be relatively limited compared to other areas, these examples demonstrate the application of anomaly detection in security, public transportation, and smart agriculture, highlighting the potential for further exploration and development in this field.

Table 2 presents an overview of the detected anomalies, along with their corresponding classification and the specific sensors used in each case. This table offers insights into the diverse range of anomalies that have been successfully identified through various sensor applications.

3.4 Limitations of Non-vision Sensors

The utilization of networks of non-vision sensors has provided many advantages. However, non-vision sensors used in the previous anomaly detection studies still have unique limitations.

First, non-vision sensors can be affected by noises produced by the surrounding environment and other sensors [37, 51], and therefore, the results are not highly accurate, and false alarms are repeatedly raised [51]. Another limitation is that they can only detect measurable properties, and in multiple cases, simple sensors cannot detect some parameters. In addition, they generate raw data that lack meaning. Another critical challenge is the uncertainty factor in some measured data. In addition, multiple scenarios require a user to wear a sensor to collect data, which can cause discomfort. In Table 3, we present several use cases that used non-vision sensors in different tasks and highlight limitations found in each use case.

4 VISION-BASED ANOMALY DETECTION

Camera and computer vision have been utilized in various video surveillance applications for safety and security. In surveillance systems, a primary objective is often to identify abnormal behavior or anomalous observations [95]. A substantial body of research has been dedicated to anomaly detection using images and videos. Visual data captured by cameras contains a wealth of

Table 2. Summary of Non-Vision-Based Anomaly Detection

Space	Reference	Anomaly	Anomaly Type	Sensor
Outdoor	Zheng et al. [146]	High/low occupancy of parking lots	C	Parking
	Bose et al. [20]	Aggressive driver behaviour, road bumps and potholes	C	GPS and accelerometer
	Castignani et al. [26]	Risky driving maneuver	C	GPS and IMU
	Andrade et al. [6]	Road anomalies (bumps, potholes, obstacles)	P	Accelerometer
	Kong et al.[70]	Urban traffic anomalies	C	GPS
	Jain and Shah [57]	Unhealthy locations based on AQI	P	Chemical
	Maag et al. [83]	Air pollution (O_3)	C	Gas
	Roy et al.[110]	Intruder in agricultural field	P	PIR and ultrasonic
Indoor	Wijayasekara et al. [132]	Open window, high zone temperature, close air supply vent	C	Temperature
	Chou and Telaga [35]	Predicted data is more/less than 2 SD for at least 5 minutes	P	Smart meter
	Zhang et al. [141]	Difference between predicted and actual value > 0.4°C	P	Temperature, light, humidity, pressure, magnetic
	Shin et al. [114]	Seizures, weakness, fall, diabetic patient with hypoglycemia, unresponsive person, altered mental status, osteoporosis, arthritis	C	Infrared motion
	Zhu et al. [147]	Spatial anomaly, timing anomaly, duration anomaly, sequence anomaly	Spatial, timing, and duration = P. Sequence = C	Motion
	HsuChen-Yu et al. [55]	Insomnia, sleep deprivation	C	FMCW radio, antenna array
	Moore Jimmy et al. [87]	$PM_{2.5}$ spike	C	Air quality with optical
	Arifoglu and Bouchachia [10]	Repeating activities, disruption in sleep, and confusion	Repeating = L. Disruption in sleep and confusion = C	Motion, door
	Dahmen and Cook [39]	Fall, nocturia, muscle weakness, depression-related behavior	C	Motion, light, temperature, door
	Ramapatruni et al. [107]	Access to the closet, the stove is on, the door is open, turning switches on manually (when the resident is out)	C	Smart plugs, wireless tags, voice assistant, smoke and CO
	Maag et al. [83]	Air pollution (CO_2)	C	Gas
Transitional	Torkamani et al. [124]	Skimming attack on ATMs	C	Vibration and voltage
	CHEN et al. [32]	Anomaly in passenger flow in subway station	C	RFID, NFC tags, magnetic
	Torkamani et al. [124]	Anomaly in passenger flow in subway station	C	RFID, NFC tags, magnetic
	Nandi et al. [90]	Passenger physical discomfort	C	Pressure
	Yang et al.[139]	Greenhouse anomaly data	C	Temperature, humidity, CO_2, soil temperature, soil humidity

Note: We denote point anomaly as **(P)**, context anomaly as **(C)**, and collective anomaly as **(L)**.

information compared to data from other sources. This rich information can be leveraged for scene understanding and subsequent abnormality detection.

This section aims to identify anomalies in vision-based anomaly detection across outdoor, indoor, and transitional spaces. Furthermore, we will discuss the types of anomalies and the vision sensor employed in each case. Additionally, we will provide a summary of vision-based anomaly detection systems, categorize anomalies, and list the corresponding sensors used in Table 4. Lastly, we will highlight the limitations associated with vision sensors.

4.1 Outdoors Anomaly Detection using Vision Sensors

Multiple studies have investigated road anomaly detection, exploring various scenes such as roads, junctions, areas around buildings, pedestrians' walkways, and parking lots. For instance,

Table 3. Limitations of Non-Vision Sensors in Multiple Use Cases

Sensor	Use case	Limitations
Motion	• Detect presence and occupancy	• Inability to distinguish multiple people or detect presence if the person is not moving [14] • Inability to distinguish animal [53]
	• Detect abnormal behaviour in daily activities [147]	• Uncertainty caused by data limited dimensions [147]
Infrared motion	• Identify human actions [27, 100, 104]	• Difficult to maintain • Inability to detect specific actions, e.g., cooking [127]
Temperature	• Measure temperature to detect open window, high zone temperature, and close air supply vent [132]	• Affected by heat from surrounding sources • Unable to identify temperature source
Wearable sensors	• Detect anomalies [1, 100, 108]	• Cause inconvenience to elderly [51] • Elderly hesitant/forget to wear sensors [48, 127] • Difficulties in charging batteries [51, 127]
Pressure-sensitive floor tiles	• Track human locations [130]	• Installation and maintenance is challenging [127]
Electrical panel and power analyser	• Recognize resident activities using home appliances load "signature" [15]	• Detection limited to activities require electricity • Unable to distinguish appliances of same model • Accuracy affected by power fluctuations [15]
CO_2	• Calculate density in indoor places [69]	• Low estimation accuracy [69]

Vorapatratorn et al. [128] proposed a system to detect obstacles in outdoor environments, aiming to assist visually impaired individuals.

In the context of public transportation, the issue of violating stop signs is discussed in [135], while traffic accident detection has been investigated in [140]. Illegal U-turns have been detected in [33, 62]. Non-pedestrians on walkways were identified by Cheng et al. [33]. Several research studies have addressed abnormal human behavior in roads and outdoor environments, including jaywalking [33, 62], fighting, and throwing objects [121].

In security and surveillance, intruders were detected in [94], where an intruder can refer to either a person or a vehicle. Four application zones were defined, such as "no human" or "no-fly" zones, with specific objects identified as intruders within each zone. Bozcan and Kayacan [21] categorized anomalies in critical environments, including objects that violate private or public rules of an environment, as well as rare object appearances that raise suspicion. Bhambani et al. [17] detected face mask violations and social distancing breaches in real-time within public places. Mehta et al. [85] successfully detected fires and guns using videos from Closed-Circuit Television (CCTV) cameras. Additionally, Lin et al. [78] identified abnormal events, defined as “irregular operations,” on construction sites based on action sequences and cycle times.

4.2 Indoors Anomaly Detection using Vision Sensors

As previously mentioned, most implemented technologies are in AAL. Vildjiounaite et al. [127] implemented illness recognition to distinguish between normal and illness days. Fall incidents were detected in [44, 49, 72, 129]. Ahmed et al. [2] detected patients’ discomfort. Khan et al. [64] identified agitation episodes in people with dementia. For building management, Hsieh et al. [54] proposed a system to detect unusual scene changes, analyzing three abnormal senses: (1) abandoned objects, (2) lost objects, and (3) opened doors. Similarly, unattended objects were identified in [97] to improve security and prevent terrorism. Abnormal human events in crowds (e.g., changing direction, sudden speed, or escape) were detected in [41, 52]. Note that the presented approaches in the previous two works also experimented with outdoor scenarios. Kakillioglu et al. [61] performed building inspection to identify thermal leakage areas.

4.3 Transitional Space Anomaly Detection using Vision Sensors

In the transportation field, Zhao et al. [145] developed an algorithm to detect unusual events in a subway station. For the subway exit, they defined three types of anomalies: (1) people walking in the wrong direction, (2) people waiting for extended periods without apparent purpose, and (3) various activities including unexpected stops, looking around, cleaning a wall by a janitor, and quickly alighting from a train and boarding again. For the subway entrance, they identified five types of anomalies: (1) people walking in the wrong direction, (2) people waiting for extended periods without apparent purpose, (3) people passing without payment, (4) exceptional communication between individuals, and (5) various activities including unexpected stops and fast running. Additionally, Kim et al. presented the detection of threat objects (e.g., motorcycles or cars) on passengers while boarding or alighting a bus [68].

In the security and surveillance field, Nar et al. [91] explored the utilization of posture recognition to identify abnormal activities in ATMs. They defined three abnormal postures: (1) aggressive posture, (2) attempts to block the camera, and (3) peeping posture.

Table 4 offers a comprehensive overview of vision-based anomaly detection, showcasing the detected anomalies, their respective classifications, and the specific sensors utilized for each case.

4.4 Limitations of Vision Sensors

Vision sensors are experiencing significant advancements in both hardware and algorithms, enabling complex vision tasks such as image classification, image segmentation, and object detection. However, despite these advancements, vision sensors still have several limitations. One of the critical challenges is privacy concerns. Individuals may be hesitant to undergo visual observation to safeguard their privacy, thus restricting the use of vision sensors to specific scenarios. Additionally, vision sensors can be costly compared to non-vision sensors and demand greater computing resources due to the high-dimensional data they generate. In this paper, we review multiple works and use cases to identify specific limitations associated with deploying vision sensors. The limitations identified are summarized in Table 5.

5 ANOMALY DETECTION TECHNIQUES

There exists a wide range of techniques for addressing anomaly detection. The formulation of the problem and the definition of anomalies and features vary across different applications. Researchers have adopted diverse methodologies based on the specific task, environment, and desired accuracy. Machine learning techniques have recently gained prominence in developing many anomaly detection approaches [92]. In this section, we identify the detection techniques employed in the previous works introduced in Sections 3 and 4. These techniques can be classified based on various criteria, including learning style (i.e., supervised or unsupervised) and their functional similarity. We categorize the techniques according to their working methods [28, 111] (see Figure 4). Additionally, we provide a comparison of the techniques used in previous works, highlighting their respective advantages and disadvantages in Table 6.

Statistical-based Techniques: Statistical anomaly detection techniques utilize a stochastic process to estimate the parameters of a stochastic model when fitting the given data. An anomaly is defined as any data point that does not belong to the stochastic model [8]. Statistical-based methods encompass the Gaussian distribution [78] (including Gaussian process regression (GPR) [33]), Multivariate Normal distribution (MVN) [26], Regression models (such as Autoregressive Integrated Moving Average (ARIMA) [35] and Logistic Regression (LR) [91]), Bayesian networks (BN) [41, 147]

Table 4. Summary of Vision-Based Anomaly Detection

Space	Reference	Anomaly	Anomaly Type	Sensor
Outdoor	Vorapatratorn et al. [128]	Obstacles	P	RGB-D sensor in Microsoft Kinect
	Xuan Mo et al. [135]	Violating stop sign	L	Video camera
	Yun et al.[140]	Car accidents	C	Video camera
	Cheng et al. [33]	Illegal u-turn, non-pedestrians on walkways, jaywalking	C	Video camera
	Kaltsa et al. [62]	Illegal u-turn, jaywalking	C	Video camera
	Tang et al. [121]	Fighting, throwing something	P	Video camera
	Nayak et al. [94]	Intruder	C	IP camera
	Bozcan and Kayacan [21]	Object violates private or public rules, rare object appearance	C	Drone camera
	Bhambani et al. [17]	Face mask and social distancing violation	C	Public images dataset (RGB camera)
	Mehta et al. [85]	Fire and gun	P	Public images dataset (RGB camera) and CCTV camera
	Lin et al. [78]	Irregular operations in construction sites	C	Camera
Indoor	Vildjiounaite et al. [127]	Illness	C	Depth camera
	Galvao et al. [44]	Fall	C	Microsoft Kinect camera and accelerometer
	Gunale and Mukherji [49]	Fall	P	Depth camera
	Ahmed et al. [2]	Patient's discomfort	P	IP-based RGB camera
	Khan et al. [64]	Agitation in people with dementia	C	Video camera
	Wang et al. [129]	Anomalies in daily activities e.g., fall	P	Mobile camera
	Hsieh et al. [54]	Abandoned objects, lost objects, opened door	P	Mobile camera
	Ogawa et al. [97]	Abandoned objects	C	Pan-tilt camera
	Hao et al. [52]	Anomalous human events	P	Surveillance camera
	Dotti et al. [41]	Abnormal human motion	C	Video surveillance camera
	Leite et al. [72]	Fall	C	Two public datasets (Microsoft Kinect, RGB cameras)
	Kakillioglu et al. [61]	Heat leakage	C	Thermal camera
Transitional	Zhao et al. [145]	People behaviour in subway station	C	Surveillance camera
	Kim et al.[68]	Threat objects (e.g., motorcycles or cars)	C	Camera
	Nar et al. [91]	Aggressive posture, blocking camera, peeping posture	P	Kinect with RGB camera

Note: We denote point anomaly as **(P)**, context anomaly as **(C)**, and collective anomaly as **(L)**.

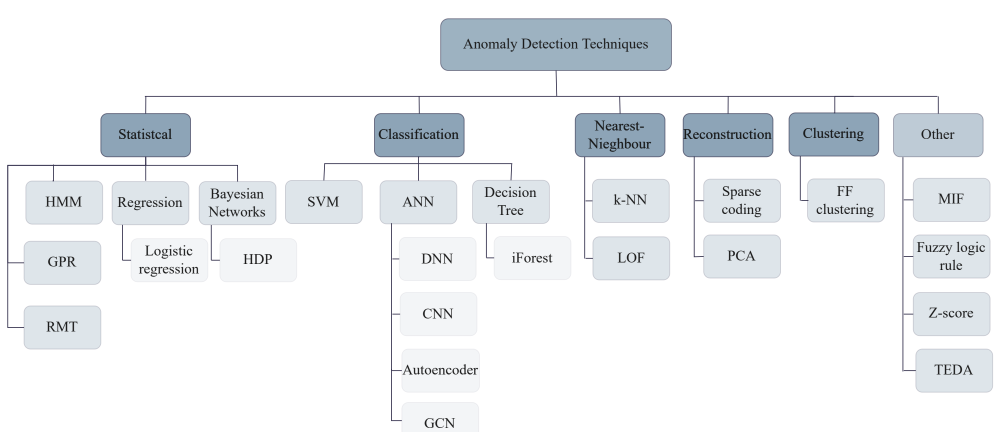

Fig. 4. Categories of Anomaly Detection Techniques [28, 111].

(including Hierarchical Dirichlet Process (HDP) [62]), Hidden Markov Model (HMM) [107, 127], and Random Matrix Theory (RMT) [32].

Table 5. Limitations of Vision Sensors in Multiple Use Cases

Sensor	Use case	Limitations
Camera	• General	• Vision sensor resolution can affect the detection and identification accuracy
	• Fall [72]	• Privacy issues [51] • Affected by environmental conditions such as dark lighting • Hard to detect objects outside the sensor installation region
	• Behavioural anomaly detection [147]	• Computationally costly [147] • Degraded performance in poor lighting and occlusion
	• People detection and tracking [120]	• Unable to track people who are largely occluded • Require multiple cameras, which can be costly
	• Localization [118]	Sensitive to changes in viewpoint and illumination [118]
Video camera	• Recognising human actions [127] • Productivity analyses [45]	• Affected by variations in light • Need line of sight
3D Depth camera in Microsoft Kinect	• Fall [72]	• Kinect sensing area is limited to 0.4 - 3 m [51]
CCTV camera	• Car accident detection	• limited distance of vision
Aerial imaging	• Object Detection [138]	• Difficult to detect small, cluttered, and rotated objects [138]
Smart camera (i.e., an embedded image sensor with processing capabilities)	• Person Tracking [123]	• Restricted memory and power consumption [123]

Classification-based Techniques: In classification-based approaches, a model learns from a labeled dataset and then categorizes data into either the normal or anomalous class. Examples of classification-based methods include Support Vector Machine (SVM) [20, 39, 44, 49, 57, 70, 90, 114, 127, 146], Artificial Neural Networks (ANN) [57, 83, 141] (including Deep Neural Networks (DNN) [21], Convolutional Neural Network (CNN) [2, 10, 17, 55, 72, 85, 94], Autoencoder [41, 64], Graph Convolutional Network (GCN) [121], and Multilayer Perceptron (MLP) [44]), as well as decision trees (including isolation Forest (iForest) [39, 139]).

Nearest-neighbour-based Techniques: These techniques operate on the assumption that normal data points tend to have close neighbors in dense neighborhoods, while anomalous points are farther away from their neighbors. Nearest-neighbour-based techniques include k-Nearest Neighbors (k-NN) [39, 44] and Local Outlier Factor (LOF) [39, 133].

Reconstruction-based Techniques: In reconstruction-based techniques, normal data is represented in a lower-dimensional space to distinguish between normal and abnormal data using reconstruction algorithms. The reconstruction error is then used as an indicator of anomalous data. Methods such as sparse coding [135, 145] and Principal Components Analysis (PCA) [39] fall under the category of reconstruction algorithms.

Clustering-based Techniques: Clustering-based techniques involve algorithms that group data points into clusters based on their structural similarity. Anomalies are identified as data points that do not fit into any normal cluster. An example of a clustering-based technique is the Farthest First (FF) clustering algorithm [146].

Other Techniques: There are several other methodologies that do not fall into the previously mentioned categories but have been employed for anomaly detection. In [140], the Motion Interaction Field (MIF) was used to model the interaction between moving objects (vehicles) in a traffic scene. A symmetric field structure, as indicated by a designed kernel function using Gaussian functions, represents a normal scene, while non-symmetric interaction indicates an anomaly. Fuzzy logic rules combined with Nearest Neighbor Clustering (NNC) in [132] to model normal behavior.

Table 6. Comparison of Anomaly Detection Techniques

Approach	Technique	Reference	Pros	Cons
Statistical	Gaussian (GPR)	Lin et al. [78] Cheng et al.[33]	• Can handle noisy data • Detect local and global anomaly • Can handle complex scenarios	• Computationally costly • Unable to detect stationary objects
	(MVN)	Castignani et al.[26]	• No need for a threshold to detect anomaly • Can be continuously retrained	• Need to address data heteroscedasticity
	Regression (ARIMA, LR)	Zhu et al.[147] Kaltsa et al.[62]	• Simple and train quickly • Able to scale features automatically	• Inefficient with non-linear data • Prone to overfitting
	BN (HDP)	Chou and Telaga[35] Dotti et al.[41] Nar et al.[91]	• Availability of alternative model • Number of topics determined automatically from data	• Inability of real-time detection • Complex implementation
	HMM	Vildjiounaite et al. [127] Ramapatruni et al. [107]	• Unsupervised approach • No need for large amount of training data • Able to sequence learning	• Dependant on features and model states
	RMT	CHEN et al.[32]	• Powerful in analyzing high-dimensional multivariate data	• Selection of a moving window and a threshold is challenging
Classification	SVM	Shin et al.[114] Zheng et al.[146] Jain and Shah[57] Vildjiounaite et al.[127] Bose et al.[20] Galvao et al. [44] Gunale and Mukherji[49] Leite et al.[72] Nandi et al.[90] Kong et al.[70] Dahmen and Cook[39]	• Capable of generalization • High accuracy • No need for significant training data	• Difficult to detect unseen data • Affected by a selection of kernel function parameters • Low performance with big datasets
	ANN (DNN, CNN, Autoencoder, GCN, MLP)	Jain and Shah[57] Maag et al.[83] Zhang et al.[141] Bozcan and Kayacan[21] HsuChen-Yu et al.[55] Nayak et al.[94] Arifoglu and Bouchachia[10] Leite et al.[72] Bhambani et al.[17] Dotti et al.[41] Mehta et al. [85] Ahmed et al.[2] Khan et al.[64] Tang et al.[121] Galvao et al. [44]	• Automatic features extraction • High accuracy • Ability for real-time detection	• Computationally costly (time) • Prone to overfitting • Need large amount of training data
	Decision Trees (iForest)	Dahmen and Cook [39] Yang et al.[139]	• Automatic features selection • Detects complex anomalies • Can handle both univariant and multivariant datasets	• Model can be complex • Less accuracy on minority classes (i.e., classes with fewer data points)
Nearest-Neighbour	k-NN	Galvao et al. [44] Dahmen and Cook[39]	• Can handle non-linear and massive data • Can handle noisy data	• Less accuracy on minority classes (i.e., classes with less data points) • Computationally costly (time) • Performance relies on parameter K
	LOF	Wu et al.[133] Dahmen and Cook[39]	• Applicable in multiple setups • Capable of generalization • Require one parameter	• Difficult to explain the reason for selecting the anomaly • Sensitive to data variability
Reconstruction	Sparse coding	Zhao et al. [145] Xuan Mo et al. [135]	• Unsupervised approach	• Inability to detects multiple objects anomalies
	PCA	Dahmen and Cook[39]	• Able to transform high dimensional data to lower dimensional • Fairly simple	• Work strictly with numeric values • Prone to missing some data

Table 6 (Continued)

Approach	Technique	Reference	Pros	Cons
Clustering	FF clustering	Zheng et al. [146]	• Unsupervised approach • Can handle large datasets	• Classify clusters with less data points as anomaly • Inefficient with non-globular clusters
Other	MIF	Yun et al. [140]	• No learning or object tracking required	• Limited application area
	Fuzzy logic	Wijayasekara et al. [132]	• Can handle uncertainty in data • Allow natural linguistic representation • Reasoning in the same way as human	• Manual definition • Approximate reasoning • Inability to receive feedback on training
	Z-score TEDA	Moore Jimmy et al. [87] Andrade et al.[6]	• Easy to implement • Unsupervised approach • Suitable for time series data • Require less computation resources	• Suitable for large datasets • Performance accuracy affected by problem formulation and selected features

The Typicality and Eccentricity Data Analytics (TEDA) anomaly detection algorithm [7] was employed in [6]. In [54], anomaly detection was formulated as a scene-searching problem, where a spider-web map was used to detect abnormal changes in a video scene. The Random Sample Consensus (RANSAC) approach was utilized in [128] to extract obstacles from the background.

Abandoned object detection was addressed in [97], where an extended ST-Patch was used to define the region of the abandoned object. A Deep Neural Network (DNN) was then employed to detect the presence of a human in the region, and if there is no human, the object is classified as abandoned. Fast Dynamic Time Warping (FastDTW) was implemented in [20] for local recognition of aggressive behavior.

For specific applications, authors have developed custom algorithms. In [87], an online peak detection algorithm based on Z-score [22] was used to identify spikes in $PM_{2.5}$ levels. Threat object detection in [68] involved image background subtraction and motion analysis. Thermal leakage areas were located using edge detection and abnormal temperature change detection in thermal images in [61]. Image entropy was utilized for detecting anomalous human events in [52], and OpenPose [25]-based algorithms were employed in [129].

Combined Techniques: In some previous works, a combination of multiple approaches or the use of multiple classifiers has been employed for anomaly detection.

In [35], authors utilized a model consisting of Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Average (ARIMA) to predict power consumption. Anomalies were defined as states with energy consumption deviating by 2 Standard Deviations (SD) above or below the predicted values for a duration of five minutes or more. A similar approach was adopted in [141], where ANN was employed to predict temperature values in a building, and posterior probabilities were calculated to identify anomaly data.

Authors in [133] utilized an ensemble algorithm that integrated the Poisson distribution, Local Outlier Factor (LOF) algorithm, and Grubbs criterion for anomaly detection. In [41], an autoencoder and a Bayesian Network (BN) module were combined to perform anomaly detection.

In [121], irregular behavior was identified by comparing a predicted human pose with the actual pose in a frame. Motion Prediction Graph Convolutional Network (MP-GCN) was used for pose prediction. Box Plot method [122] in combination with Gaussian distribution was employed by Lin et al. [78] to define irregular operations.

Furthermore, in addition to employing the Isolation Forest (iForest), Yang et al. [139] combined it with Locality-Sensitive Hashing (LSH) for anomaly detection.

6 COMPUTER VISION SYSTEMS

The deployment of cameras is becoming increasingly common for computer vision and surveillance tasks. Camera sensors provide a means to generate data that can be used to understand activities, behaviors, and environments. These data have been utilized in various security and elderly care applications. Vision-based anomaly detection, which is a sub-domain of computer vision, leverages camera sensors for anomaly detection [137].

Our objective in investigating computer vision systems is to understand how camera sensors have been employed in these systems and highlight their capabilities. Additionally, we aim to identify the capabilities that have the potential to be reused in our vision of implementing hybrid sensor-based anomaly detection.

In this section, we delve into the hierarchy of computer vision systems in Section 6.1. Subsequently, we explore the implemented approaches within these systems in Section 6.2.

6.1 Computer Vision Processing Hierarchy

In this section, we explore the hierarchy of computer vision systems to highlight the capabilities of each system in accomplishing tasks such as object recognition and behavior analysis. Computer vision systems exhibit diversity in terms of architectures (e.g., centralized, distributed), approaches, and the tasks they can accomplish. However, many computer vision applications share a common system scheme with distinct stages.

The typical hierarchy of a computer vision system is divided into three levels: low-level vision, mid-level vision, and high-level vision [93].

Low-level vision encompasses multiple steps aimed at achieving the task at hand. These steps involve extracting basic image parameters for further processing. Examples of low-level stages in previous camera systems include feature extraction [23, 31, 50, 65, 73, 82], scene decomposition [73], and face detection [65].

Mid-level vision follows the low-level stage and involves tasks such as object localization and classification [19], motion transformation (i.e., transferring features into low-dimensional address codes) [23], and image classification [50].

High-level vision represents the final task and utilizes the output of the previous stages. Operations such as people counting [82], distributed object recognition [31], multiple people tracking in smart camera networks [123], anomaly detection [73], and target finding [65] are classified as high-level tasks. Additionally, the surveyed systems accomplish other high-level tasks, including providing video summaries in multi-camera systems [73], identifying products in supermarkets [19], utilizing crowds to answer users' questions in real-time [50], and recording videos when a fiducial mark is detected [74]. In Figure 5, the relationship between vision-based anomaly detection and computer vision systems is illustrated. In the context of vision-based anomaly detection (Figure 5(a)), preprocessing is a low-level vision task (Figure 5(b)), analysis is a mid-level vision task, and anomaly detection is a high-level vision task. This demonstrates how vision-based anomaly detection fits within the broader framework of computer vision systems.

Table 7 provides an overview of vision-related tasks at different levels in previous works. This table compares the tasks involved in vision-based anomaly detection with the tasks performed in computer vision systems. By examining these tasks, we can identify similarities and shared capabilities that can contribute to the implementation of a hybrid sensor-based anomaly detection system.

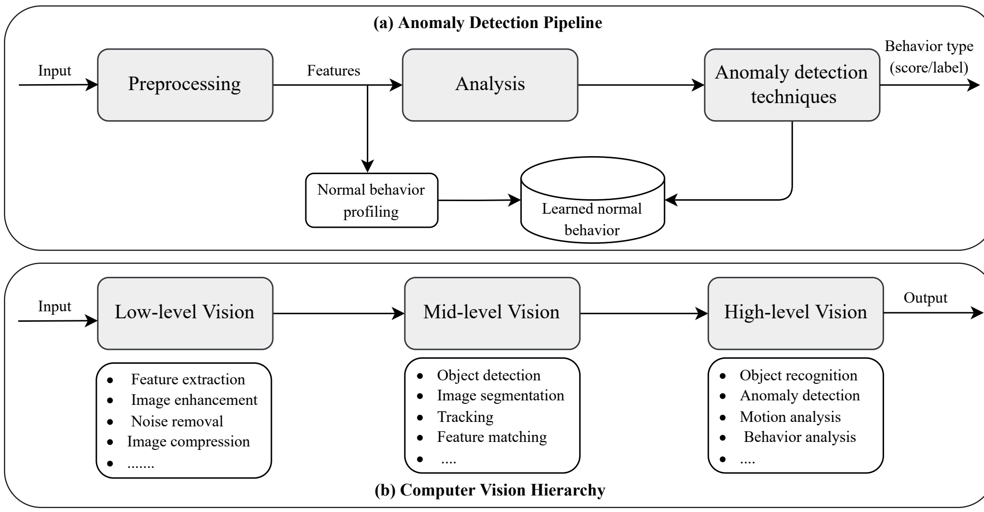

Fig. 5. Relationship between vision-based anomaly detection and computer vision systems. (a) Typical anomaly detection pipeline [111]. (b) The computer vision system hierarchy presents low-level, mid-level, and high-level vision with examples of each level's tasks.

6.2 Computer Vision Processing Approaches

The reviewed literature utilized diverse techniques to accomplish the desired task. Some researchers address fundamental problems. Others tackle specific data processing task which requires a series of sub-tasks. For instance, locating a target needs feature extraction, face detection, and calculating feature similarities to obtain the result.

Due to the diversity of problems and solutions investigated in the previous studies, it isn't easy to present a general classification of their methods. In this work, we introduce techniques used to achieve the following common tasks:

– Feature extraction: Extracting useful features to define an object is a core component in the image processing pipeline. Researchers followed several techniques to extract features and reduce dimensionality. Techniques include histogram of oriented gradients and local binary patterns [82], SIFT [31], dense optical flows results [73], ResNet50 [50], CNN [65].
– Object detection and classification: object detection refers to identifying object features or patterns in an image (e.g., identifying people). Sorting these objects into categories is classification (e.g., determining whether a person is wearing a mask). Previous studies include tasks such as human detection [23, 82], face detection [50, 65], recognize products and notes [19], recognize general objects [31], and image classification [19, 31, 50]. Techniques to implement object detection and classification include a combination of Multiple instance learning (MIL) and linear SVM [82], Single Shot Detector (SSD) [19], multitask cascaded convolutional networks [50], KNN classifier [50], and Haar feature-based cascade classifier from the Open computer vision library [65].
– Tracking: After recognizing an object of interest in many applications, the model keeps tracking the object as they move in the video frame. To track an object, authors in [123] used the tracking algorithm presented in [89] which merges Bayesian particle filters and the Dempster–Shafer theory, and in [23], they employed a framework composed of association based tracking [60, 136] and category free tracking [46, 79, 115] approaches.

Table 7. A Summary of Tasks in Computer Vision Systems at the Low, Mid, and High Levels

Level	Task	Reference
Low-level tasks	Feature extraction	Ma et al.[82] Chen et al. [31] Leo and Manjunath [73] Boldu et al. [19] Cao and Wang [23] Guo et al. [50] Khazbak et al. [65]
	Calculate suitability value v(S) with each camera set	Tessens et al. [123]
	Scene Decomposition	Leo and Manjunath [73]
	Pedestrian detection	Cao and Wang [23]
	Face Detection	Khazbak et al. [65]
Mid-level Tasks	Occlusion handling	Ma et al.[82]
	Joint decoding	Chen et al. [31]
	Selecting cameras set	Tessens et al. [123]
	Activity Motif Discovery Motif Part Selection Topology Discovery Activity Importance	Leo and Manjunath [73]
	Object localization and classification	Boldu et al. [19]
	Human pose detection Motion transformation Face detection and blurring	Cao and Wang [23]
	Image duplicate checking Image classification	Guo et al. [50]
	Detect fiducial mark	Li et al. [74]
	Calculate features similarity	Khazbak et al. [65]
High-level Tasks	People counting	Ma et al.[82]
	Distributed image and video processing Event (motion) detection	Chen et al. [31]
	Multicamera multiperson tracking	Tessens et al. [123]
	Video summarization Anomaly detection	Leo and Manjunath [73]
	Recognize products and notes	Boldu et al. [19]
	Private human addressing in public	Cao and Wang [23]
	Answering natural language user questions	Guo et al. [50]
	Human behaviour analysis	Li et al. [74]
	Locate targets	Khazbak et al. [65]

Note: Similar tasks in computer vision systems and vision-based anomaly detection

7 HYBRID SYSTEMS: INTEGRATION OF VISION AND NON-VISION SENSORS

In hybrid systems, multiple components combine to accomplish a task, including frameworks, sensors, algorithms, and protocols. Consequently, researchers have investigated the feasibility of developing hybrid systems. In our work, we focus on reviewing sensor-based hybrid systems to explore the effects and opportunities of combining multiple sensors within built environments.

First, we introduce general hybrid applications that utilize various sensors in multiple domains in Section 7.1. Next, in Section 7.2, we present hybrid sensor-based systems specifically designed for anomaly detection. Finally, we identify possible opportunities for employing vision and non-vision sensors for anomaly detection in Section 7.3.

7.1 Hybrid Sensor-based General Applications

Several authors have explored the feasibility of combining various sensors to accomplish different tasks. For example, data from multiple sensors, such as camera, radar, and LiDAR, was employed to detect objects in [29, 34, 76, 109]. Multi-sensor object detection is commonly implemented in autonomous driving and robotics applications.

Indoor localization through sensor fusion was investigated in [16, 105, 106, 148]. Sensors used for indoor localization include cameras, GPS, IMU, and WiFi signals. Activity recognition is another common application that utilizes hybrid sensors [5, 47, 67, 96]. Furthermore, medical image fusion, which involves integrating multiple images from various imaging sources, has received growing interest in providing accurate diagnoses of medical issues [12, 56, 75].

These approaches have exhibited substantial accuracy. Therefore, we believe that exploring hybrid sensor-based anomaly detection is worthwhile.

7.2 Hybrid Sensor-based Anomaly Detection

Different types of sensors have been used independently to detect anomalies. Sensors such as temperature, light, accelerometer, and camera have been employed to identify outliers. Non-vision sensors have limitations, including vulnerability to environmental noises. Vision sensors also face challenges, such as privacy concerns and light sensitivity. Hybrid sensor-based anomaly detection emerges as a promising solution to mitigate these limitations.

In our context, a hybrid sensor-based anomaly detection system fuses data from different sensors (vision and non-vision) to develop a detection model. While there have been a few applications that utilize multiple non-vision sensors, such as GPS and accelerometer [20] for detecting aggressive driving patterns and a diverse set of sensors for monitoring the health of older adults [39, 119], the exploration of hybrid sensor-based anomaly detection that combines vision and non-vision sensors remains limited in the literature.

We believe that a hybrid approach for anomaly detection allows for leveraging the strengths of both vision and non-vision sensors and enriches the overall detection decision. For example, in [51], researchers utilized an IR-UWB radar sensor and an IP camera to collect data for training a fall detection model. The IP camera was exclusively used to provide labeling for developing a classifier, while the application predicts movements using IR-UWB alone. Their technique achieved promising results, prompting further exploration of the hybrid approach.

To the best of our knowledge, the feasibility of hybrid sensor-based systems that combine vision and non-vision sensors for anomaly detection has not been extensively investigated in the literature. Therefore, we plan to explore this area and assess its potential. Figure 1 illustrates the domain of hybrid sensor-based anomaly detection.

7.3 Opportunities for Hybrid Sensor-Based Anomaly Detection

Vision and non-vision systems have their own advantages and disadvantages, with each being better suited for certain applications. However, hybrid sensor-based anomaly detection presents numerous opportunities to improve performance and overcome the limitations of current systems.

Several methods combine vision and non-vision sensors to detect anomalies in built environments. We identify two types of opportunities: deployment and training (see Figure 6).

In deployment opportunities (Figure 6 (1)), vision data is used to train the anomaly detection model and contributes to the decision-making process.

In training opportunities (Figure 6 (2)), one type of sensor (either vision or non-vision) is used with a pre-trained anomaly detection model solely for labeling other sensor data, without being directly involved in the decision-making process. The opportunities for developing hybrid sensor-based anomaly detection systems are as follows:

(1) *Deployment opportunities:*
   (a) Default approach: The default approach involves collecting data from both non-vision and vision sensors, labeling them, and training a model with the combined dataset. Figure 6(a) illustrates using a hybrid system to detect an open window anomaly. Magnetic

sensor data are collected and labeled as ground truth, while temperature, humidity, pressure, and camera data are collected and labeled for training the hybrid sensor-based anomaly detection model. Ultimately, decisions are made using data from all sensors.
   (b) Privacy-sensitive approach: In the privacy-sensitive approach, the anomaly detection model is trained using data from non-vision sensors and separately using data from vision sensors. The confidence of the decision made by the non-vision anomaly detection model is then calculated. If the confidence is high, the decision is considered final and based solely on the result from non-vision sensors. However, if the confidence is low, an ensemble model is used to combine the results from both non-vision and vision models and make the final decision. Figure 6(b) illustrates the privacy-sensitive approach in the context of the open window scenario.
(2) *Training opportunities:*
   (a) Camera to train non-vision sensors: This approach uses camera data with a pre-trained anomaly detection model to classify images. The data from non-vision sensors are then collected and labeled based on the class assigned in the previous step. Subsequently, the hybrid anomaly detection model is trained using this labeled data, and the decision is made solely based on the data from non-vision sensors. Figure 6(c) illustrates this approach in the context of the open window scenario.
   (b) Non-vision sensors to train camera: In this approach, data from non-vision sensors are collected and employed to train an anomaly detection model, enabling data classification. Images captured by a camera are subsequently collected and labeled based on the assigned class obtained in the previous step. Finally, the hybrid anomaly detection model is trained using this labeled data, and the decision is made using only the data from the camera. Figure 6(d) depicts this approach in the open window scenario.

Hybrid sensor-based anomaly detection has the potential to make significant advancements in the upcoming years, driven by the expansion of embedded machine learning algorithms, the availability of affordable hardware, and advancements in computer vision. These factors contribute to enhancing the capabilities of hybrid techniques, enabling the detection of anomalies in diverse scenarios, and the development of fully automated detection systems.

8 RESEARCH CHALLENGES AND TEST CASES

This section explores challenges with hybrid anomaly detection in Section 8.1. Additionally, we provide researchers with test cases as a testbed for anomaly detection in Section 8.2.

8.1 Research Challenges

The widespread adoption of the IoT and sensor technologies has created abundant research opportunities and practical applications. However, despite significant advancements in sensor-based anomaly detection, there are still several limitations that need to be addressed in the context of hybrid sensor-based anomaly detection. Through a comprehensive survey of existing works in the field, we have identified the following research challenges:

- *Sensors' selection:* Due to advances in sensor hardware, software, and communication technologies, sensor heterogeneity has dramatically increased. Today's world comprises billions of sensors to measure various physical/chemical quantities. Thus, selecting a sensor for a specific application is a challenging process. Two fundamental challenges lie in selecting sensors: (1) the suitable sensor type for the proposed task, (2) the proper sensor device from multiple sensor manufacturers measuring the same property [103].

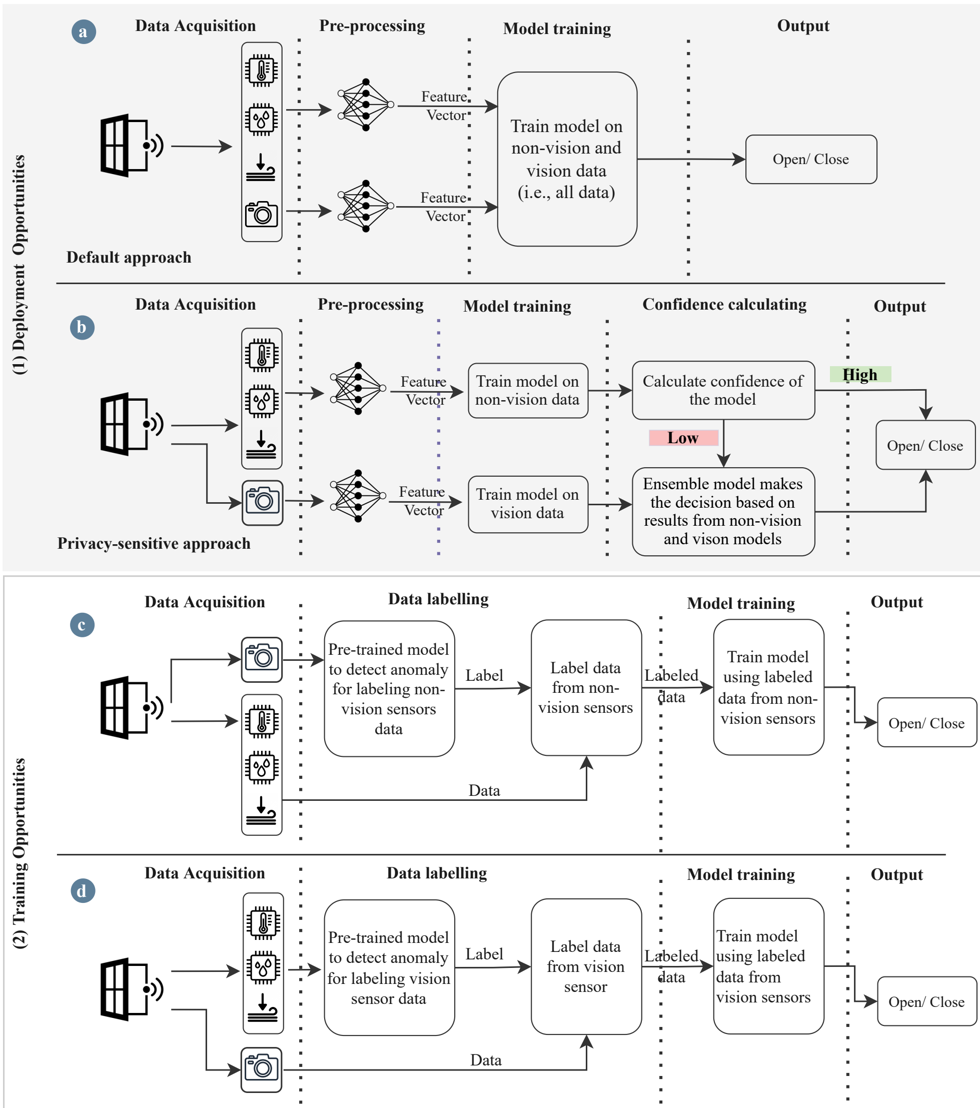

Fig. 6. A system to detect an open window (i.e., anomaly) illustrates hybrid sensor-based anomaly detection opportunities. (a) Default approach. (b) Privacy-sensitive approach. (c) Camera to train non-vision sensors approach. (d) Non-vision sensors to train the camera approach. *Notes:* (1) Non-vision sensors are temperature, humidity, and pressure in this example. (2) Magnetic sensor in the window used for ground truth data.

For the first challenge, as we highlight in the anomaly detection sections, recognizing human actions such as falls has been implemented using diverse sensors such as wearable, motion, pressure, and camera. Each sensor has its advantages and limitations. The sensor selection depends upon several factors, such as location, environmental factors (e.g., weather, illumination), context, and battery life. There are two ways to select the sensor: traditional web search and sensor selection tools. Traditional web search for manually selecting a sensor is an infeasible solution due to the diversity of sensors, the inability to find accurate sensors' characteristics, and the large scale of IoT environments. For example, forest fire detection would require a user to choose many different sensors, which can be difficult. Sensor selection tools are software solutions that automatically perform the search and selection process based on user criteria.

A fundamental reason for the second challenge is the lack of standards to develop sensors [13]. Sensors have various specifications such as sensitivity, reliability, resolution, accuracy, and offset. For example, acoustic sensors are available in several sensitivity levels based on frequency. Users can have different requirements and priorities for these specifications. Therefore, quality and ranking methods are needed to aid users in sorting sensors based on their demands. Many research proposals have addressed the selection and ranking problem and developed searching and sorting tools [13, 77, 101, 102, 113].

While employing multiple distributed sensors can provide comprehensive information and overcome the previous challenges, it has disadvantages. First, coordinating a set of sensors in indoor or outdoor environments is challenging. Second, deploying many sensors is costly, especially in large environments [39]. Furthermore, it can cause inconvenience for residents in home environments [119].

– *Privacy:* The adoption of camera sensors raises privacy concerns. Individuals are reluctant to be observed, especially in home environments, and prefer less intrusive sensors for data collection [127]. It has been found that video monitoring is primarily utilized to identify critical actions that non-vision sensors cannot recognize, such as cooking. To address privacy issues, several researchers have employed privacy-preserving hardware, algorithms, or protocols. The depth and thermal cameras are considered less invasive to privacy and can provide more reliable detection compared to non-vision sensors. Depth cameras have been used in various works for monitoring human motion in illness recognition [127], activity recognition [30, 58], and fall detection [49]. Thermal cameras have been utilized by Kakillioglu et al. [61] to detect heat leakage. Both types of cameras have demonstrated accurate results while preserving residents' privacy. Therefore, future anomaly detection systems should consider incorporating these cameras.

  In addition to hardware solutions, Cao and Wang [23] investigated the issue of private human addressing in public. They identified users based on their unique motion patterns. To maintain privacy, sensor data from users' smartphones are stored locally and not uploaded to the server. Additionally, they applied Principal Component Analysis (PCA) to transform motion features into low-dimensional address codes, preventing motion pattern leaks.

  Guo et al. [50] implemented several procedures to preserve the privacy of system users: (1) Images are transmitted to the server in low-quality (640 x 480 px), and no video or audio recordings are made. (2) Detected faces are covered with black boxes using multitask cascaded convolutional networks [142]. (3) Only small regions of interest are shown to crowd workers. In the case of target finding [65], the photo of the target is not revealed to the server or the worker. Facial information of the target and bystanders is encrypted before uploading to the server, and homomorphic encryption techniques are employed for searching matches between the encrypted target's data uploaded by a requester and a worker. Despite the various privacy-preserving approaches proposed, privacy concerns still persist and require further attention.

– *Computer vision:* Computer vision has achieved significant advancements in various domains. However, it still faces several limitations. Firstly, computer vision applications require multiple hardware components, including vision sensors (e.g., cameras), which can be costly. Furthermore, their installation requires careful planning and design to avoid blind spots and ensure effective deployment. Secondly, high-quality datasets are crucial for successful computer vision training. However, the process of collecting, annotating, and storing these datasets is challenging and expensive. Thirdly, environmental conditions such as illumination, occlusions, and background variations can compromise the quality of vision data and need to be addressed. Lastly, computer vision applications tend to have a comparatively high computational cost.

- *Sensors limitation:* As discussed in previous sections, both vision and non-vision sensors have inherent limitations. In addition to the aforementioned constraints, sensors can be sensitive to environmental changes, such as weather conditions and external heat sources. For instance, CO_2 gas sensors used for air pollution detection can be affected by gases produced through human breathing and skin oils [83]. Moreover, the spatial coverage of certain sensors is limited. Wearable sensors placed on the right hand for motion recognition, for example, can only detect movements of the right hand. Vision sensors also face challenges related to poor lighting conditions, color reflections from objects, and varying distances. Additionally, some sensors may produce a low response, low resolution, or imprecise output. The interpretation of data from certain sensors, such as sonar, can also be challenging.
  The installation and maintenance of sensors incur significant costs and require comprehensive planning. Lastly, some sensors are designed for specific environments, like indoor or outdoor settings. For example, fall detection systems utilizing ambient sensors like pressure and vibration are limited to indoor areas. Future anomaly detection applications within built environments should consider these sensor limitations.
- *Classic anomaly detection algorithms:* Several machine learning models have been developed for anomaly detection, achieving satisfactory performance in multiple scenarios. However, there are cases where the accuracy of these classic algorithms can be improved further.
  In certain research studies, authors have explored the combination of different models to achieve better performance. However, limited works have focused on integrating data from different sources (i.e., multi-modal sensor fusion) during the training process. Multi-modal sensor fusion systems aim to merge data from various sources (i.e., sensors) to enhance accuracy. This fusion can occur at three levels: (1) feature-level fusion, (2) data-level fusion, and (3) decision-level fusion. The selection of the fusion strategy depends on the specific problem, and promising classification performance results have been observed in various applications [37, 59, 116]. Exploring the integration of non-vision sensor data with camera data for training models could yield valuable insights.
- *Computation on edge:* Running machine learning algorithms demands substantial hardware resources, like CPUs, memory, and connectivity. While many applications have been deployed on PCs or cloud platforms centrally, streaming massive data from IoT devices to a central server for processing can be challenging, especially for real-time applications.
  Although a few research studies have explored the feasibility of distributed processing on the edge [19, 20, 94], they have primarily utilized single-board computers (e.g., Raspberry Pi). Deploying machine learning models on heavily constrained devices, such as microcontrollers, still presents challenges. Microcontrollers have limited computing capabilities and do not support floating-point operations. Embedded machine learning, also known as TinyML, is a promising research direction that enables running models on microcontrollers. For instance, Andrade et al. [6] proposed an embedded machine learning algorithm for detecting road anomalies, which runs on the Arduino Nano 33 IoT microcontroller and utilizes an accelerometer sensor. This effort is a promising advancement and suggests potential options for sensor-based anomaly detection on the edge.

8.2 Test Cases

Multiple cases can lead to damage to the built environment or pose harm to residents, classifying them as anomalies. Timely identification of these anomalies is crucial in order to mitigate potential hazards and ensure the safety and well-being of occupants. In this section, we begin by identifying several anomaly test cases and subsequently introduce their common properties.

Anomaly cases within built environments have been detected using a variety of sensors. We posit that combining camera sensors with other types of sensors can enhance the overall performance of anomaly detection systems. Researchers can evaluate the efficacy of their proposed anomaly detection models by measuring their functionality against the following test cases:

- *Case 1: temperature fluctuation.* Temperature plays a critical role in creating a healthy environment and ensuring occupant comfort. Daily or seasonal temperature variations can have detrimental effects on buildings in multiple ways. Firstly, temperature changes impose thermal stresses on concrete elements, leading to significant damage to the building structure [3]. Secondly, achieving satisfactory indoor temperatures has increased the demand for air conditioning (AC) systems. Different rooms and occupants require varying comfort levels, which can impact airflow dynamics [24]. Energy consumption is another aspect influenced by temperature, with heating and AC being the primary energy consumers in buildings [24, 132]. Therefore, temperature fluctuations need to be considered during the design phase and continuously monitored.
  Numerous researchers have investigated the effects of temperature and proposed solutions for monitoring and detecting temperature fluctuations. These studies have primarily utilized temperature sensors to identify such changes. As previously mentioned, temperature fluctuations can be caused by various factors, such as open windows or doors. While a temperature sensor can detect changes in degrees, it cannot accurately determine the underlying cause of these fluctuations. In such cases, camera sensors can play a crucial role in identifying the reasons behind temperature changes and enhancing the accuracy of detection.
- *Case 2: High CO_2 concentration.* Elevated CO_2 concentration contributes to poor Indoor Air Quality (IAQ) [24]. Lower IAQ in indoor environments can have various detrimental effects on people's health, including decreased attention and productivity. The human body's response to high CO_2 levels ranges from discomfort, increased breathing depth, headaches, elevated blood pressure, and dyspnea, to loss of consciousness and even death [143]. Crowded enclosed spaces are particularly prone to increase CO_2 concentrations and indoor gas pollutants. While CO_2 sensors are commonly used to address this issue, they cannot automatically differentiate between CO_2 emitted by humans and other sources, thus leading to less accurate air pollution measurements. Therefore, the integration of camera sensors can play a crucial role in detecting the presence of humans in overcrowded rooms, thereby augmenting the performance of gas sensors.
- *Case 3: Excessive humidity.* High humidity levels in buildings pose a persistent issue, increasing the likelihood of condensation. The condensation of walls can lead to destructive consequences and create an unhealthy living environment, facilitating the growth of bacteria [84]. Moreover, elevated humidity levels provide ideal conditions for mold growth [86]. Excessive humidity can stem from various factors, including moisture produced by occupants, inadequate room ventilation (particularly in winter), water leakage, or unintentionally left open windows or doors. Researchers have utilized humidity sensors to measure humidity levels. In conjunction with humidity sensors, cameras can be employed to detect open windows, or doors, thereby enhancing the overall detection capabilities.

- *Case 4: Abnormal human behavior.* This category includes activities like falls or unexpected motions. Falls are a significant cause of fatal injuries, especially among the elderly, resulting in fractures [51]. Falls can lead to loss of consciousness, and vice versa, which can have severe consequences, even death in severe cases. Extensive research has been conducted to develop fall detection techniques, broadly categorized into wearable-based, camera-based, and ambient-based approaches. Wearable devices commonly employ accelerometer sensors, while camera-based methods utilize depth cameras. Ambient devices encompass pressure, RF, ultrasonic sensors, and floor vibration-based fall detectors, each with its own strengths and weaknesses. Notably, there is a lack of research focused on integrating vision and non-vision sensors to detect falls, to the best of our knowledge.
  Human motion is typically considered routine, but in certain situations, it can be identified as anomalous. For instance, nighttime movements at home could indicate sleepwalking or intrusion, both posing safety risks. Sleepwalking is a sleep disorder where individuals unconsciously move, potentially causing harm [117]. Monitoring patients during sleep is crucial. Intruders may exhibit unexpected movements during both day and night, necessitating safety measures. Previous research used various sensors like PIR and load cells to detect movements [40], but high false positives and inability to differentiate between residents, intruders, or animals are issues. Moreover, they cannot detect sleepwalking episodes. Integrating visual capabilities with these sensors can improve classification accuracy.
- *Case 5: Household appliance accidents.* Accidents involving household appliances directly impact human life and can result in electrical shocks, fires, and other adverse effects. Monitoring the status of devices during usage and strengthening safety measures are crucial. While academia has predominantly focused on the safety of industrial appliances, limited research has been dedicated to home appliance safety [81, 134]. Incidents such as misplacement of kitchen appliances (e.g., kettle) or leaving them unattended can lead to electrical shocks or fire risks. Other incidents include faulty boilers, which can cause boiler explosions and gas leakage throughout the building. To mitigate such threats, appropriate sensors must be employed for detection. Various types of sensors, including smoke, CO_2, gas, PIR, and temperature sensors, can be utilized to detect household appliance accidents [81]. Integrating these sensors with cameras holds the potential to enhance the effectiveness of household appliance accident detection systems. Cameras can provide supplementary information and increase the accuracy of the system by capturing visual cues associated with appliance-related incidents.

The properties of anomaly cases in built environments can vary depending on the specific circumstances and context in which they occur. However, certain characteristics are commonly observed across different cases of anomalies. Table 8 presents the typical properties of building anomaly cases, highlighting factors such as the nature of the anomaly, the speed of its occurrence, and its potential impact on building performance, safety, or occupant comfort.

Internal factors, including the age of equipment, maintenance history, and design elements, as well as external factors such as temperature, occupancy patterns, and building usage, can significantly influence the occurrence and manifestation of anomalies in built environments. Therefore, it is crucial to consider the specific context and conditions of each anomaly case when analyzing and interpreting its characteristics. By taking into account these factors, practical approaches can be developed for the diagnosis, mitigation, and prevention of anomalies in the future.

Table 8. Properties of Sensor-Based Anomaly Test Cases Within Built Environments.

Property	Case 1	Case 2	Case 3	Case 4	Case 5
Sensor type	Temperature	CO_2	Humidity	Accelerometer, RF, vibration, presser, PIR, load cells, ultrasonic	Smoke, CO_2, gas, PIR, temperature
Sensor capabilities	Accuracy, fast response, wide range, durability, energy-efficient, inexpensive, easy integration, wide availability	Sensitivity, accuracy, fast response, wide range, inexpensive, reliable, easy integration	Sensitivity, accuracy, fast response, wide range, inexpensive, energy-efficient, easy integration, stability	**Accelerometer**: Sensitivity, accuracy, wide range, inexpensive, ease of installation **RF**: Wide range, imaging, reject unwanted signals, no privacy issues, easy integration, tolerance to temperatures and humidity, capacity to measure in invisible situations, comfortable to user **Vibration**: Sensitivity, wide range, multi-axis measurement, environmental tolerance, easy integration **Pressure**: Sensitivity, accuracy, inexpensive, no privacy issues, fast response, energy-efficient, small size, easy-to-use **PIR**: Sensitivity, fast response, energy-efficient, customization, people counting **Ultrasonic**: Detecting changes in sound patterns, no inconvenience to the user	**Smoke**: Sensitivity, inter-connectivity, fast response, reliability **Gas**: sensing various gases
Camera type	RGB, infrared, thermal	RGB, depth	RGB, infrared	RGB, depth, night vision, thermal	RGB, thermal
Camera capabilities	**RGB**: Computer vision features (such as image classification, object detection), accuracy, wide range, context **Infrared**: Provide temperature measurement, night vision, building inspection **Thermal**: Provide temperature measurement, night vision, building inspection, provide details for object positioning, immune to the influence of light reflections	**Depth**: Preserving privacy, accuracy, occupancy detection, people counting		**All**: Minimal disruption to everyday activities, detection of complex activities **Depth**: Gesture recognition, body tracking **Night vision**: Motion and object detection	**Infrared**: locate people in smoke-filled environment

Table 8 (Continued)

Property	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Observed area	Single object	Full room	Single object	Full room	Single/multiple objects
Feature-of-interest	Door, window	People	Door, window, tap	Person	Household appliances e.g., boiler, kettle, oven
Causing factor	Environmental conditions, human behavior, improper installation, material defects	Human behavior	Environmental conditions, human behavior, improper installation, material defects	Human behavior	Human behavior, design flaws, improper installation, lack of maintenance, outdated appliances
Nature of anomaly	Environmental, mechanical	Environmental	Environmental, structural, mechanical	Behavioural	Mechanical, behavioural
Occurrence speed	Gradual	Gradual	Gradual	Sudden, gradual	Sudden, gradual
Visual property	Pixels change in images, infrared radiation, color variation	Human presence	Pixels change in images, infrared radiation	Pixels change in images, human presence, changes in body position and orientation	Pixels change in images, color variation, red light, steam, smoke
Implications	Energy inefficiency, property damage, loss of occupants' comfort	Health Risks, loss of occupants' comfort	Health risks, property damage	Health risks, safety risks, financial losses	Health risks, safety hazards, financial losses, property damage
Detection Objective	Energy Efficiency, environmental monitoring, comfort and convenience	Health and well-being, occupancy monitoring	Energy Efficiency, environmental monitoring, comfort, and convenience	Security and safety, health and well-being	Energy efficiency, predictive maintenance, safety
Detection challenge	Calibration and maintenance, correlation with environmental factors, sensor placement, varied building design	Calibration and maintenance, sensor placement, varied room sizes	Calibration and maintenance, correlation with environmental factors, sensor placement, varied building design	May present an inconvenience to the user, privacy concerns, human variability, false positives	Sensor placement, false alarms, appliance variability, and smoke detectors can be affected by high humidity or temperature fluctuations

Notes: (1) Sensors' capabilities differ based on the sensor model and technology. (2) Anomaly nature identifies which aspects of the building it is related to. Structural anomalies, for example, are related to the building's structure, while mechanical anomalies are related to the building's mechanical systems (e.g., plumbing).

9 CONCLUSIONS

The camera sensor has found widespread use in various applications, particularly in providing surveillance functionality. In recent years, it has gained significant attention for its role in enabling computer vision tasks. Anomaly detection is a crucial application within the field of computer vision. This article aims to provide a comprehensive review of anomaly detection systems that utilize sensors in IoT environments, with a specific focus on the camera sensor.

The article begins by introducing fundamental definitions of concepts and technologies related to anomaly detection. It then proceeds to discuss the existing works in sensor-based anomaly detection over the past decade, emphasizing the use of both non-vision sensors and the camera sensor as primary components. The different approaches employed for identifying anomalies are identified and compared.

In addition to anomaly detection, the article highlights the capabilities of camera sensors in other applications, such as target finding, to provide a deeper understanding of their potential.

Furthermore, the article explores the concept of hybrid sensor-based anomaly detection and the opportunities it presents.

Throughout the review, the challenges encountered in the field are identified and discussed. The article concludes by presenting multiple anomaly test cases that can be used for evaluation in future research. The ultimate goal of the article is to establish a solid foundation for understanding the role of the camera sensor in anomaly detection and to facilitate future advancements.

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