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Review

A Survey from the Current States to the Challenges in the View of Engineering Practices: The Possibility of a Quantitative Infrared Passive Thermography Inspection of Debonding Defects in Building Clads According to the Physics Laws of Heat Conduction

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Abstract: Existing techniques for detecting wall delamination often suffer from significant safety and efficiency issues in practice. Single-frame solar infrared thermography presents a promising non-contact and non-destructive alternative. However, its current application is qualitative rather than quantitative, as its results are highly susceptible to engineering environmental factors, rendering the assessment directional rather than precise. This review examines the development of this technology over the past 30 years from a practical engineering perspective, covering its applicability, evaluation criteria, post-processing, and commercialization. We identify the core reason for the inability to provide quantitative results: the loss of temporal information regarding the surface temperature's response to the heat source. Looking ahead, this paper discusses the potential for enhancing single-frame solar thermography by integrating advancements from the last five years in AI. Specifically, we explore the feasibility of using Physics-Informed Neural Networks (PINNs) coupled with generative models to reconstruct the missing thermal response data. This approach holds significant promise for elevating single-frame solar thermography from a qualitative screening tool to a robust, quantitative method for assessing wall delamination.

Keywords: building exterior wall defect detection; thermal imaging; deep learning; detection indicators

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1 Introduction

Delamination of building envelopes results in unpredictable detaching[1], degrading the service life of a building and introducing hazards to people nearby[2]. Aging causes the delamination of building envelopes. These defects pose significant long-term threats to building safety and durability. Unfortunately, approximately 45% of the global building stock, and 60% of the building stock in some major Chinese cities, consist of buildings that are over 20 years old. In high-density urban areas like Singapore and Hong Kong, over 70%[4]-[7] of the building stock is made up of buildings over 20 years old. In Singapore, there were 92 incidents of falling components from high-rise residential facades between 2021 and 2023, with 71% attributed to delamination and hollowing between tiles and their

substrate. In severe cases, this may trigger accidents such as wall spalling or localized collapse.

Thermography inspection provides a quick, field-wise and contactless inspection to the building envelope. Unlike traditional inspection methods, such as manual tapping, ultrasonic testing, and Ground Penetrating Radar (GPR), requiring point-by-point contact testing, thermography can be carried by an unmanned aerial vehicle (UAV) to complete a quick inspection of a ten-floor residential building within hours rather than 7 to 10 days[8]. Similar to visible light vision, thermography can identify minute surface cracks in walls[9]. Existing studies show that IRT can achieve an over 85% accuracy in identifying concrete-reinforcement interface delamination[10]. With Principal Component Analysis (PCT) and Pulsed Phase Thermography (PPT), detection capacity has been increased by about 15% to 52%, enabling identification of deeply buried small defects with a diameter-to-depth ratio as low as 1.0. Thanks to the development of infrared cameras, there are over 500 firms getting infrared certifications on building inspections. Hongkong Concrete institute (HKCI) has held special chapter for thermography inspection of building walls. The mainland of China, Hongkong, Singapore, Europe and the United States have already built a set of standards on practices and personnel.

However, existing thermography techniques face multiple practical challenges in practical quantitative detection of envelope defects. For example, existing studies show that orientation will affect the optimal sampling window of thermography relying on solar radiation[3]. Insufficient data accumulation hinders the establishment of full-cycle predictive models spanning from 'micro-damage' to 'structural failure,' thereby failing to provide scientific grounds for early intervention. Moreover, thermal images are susceptible to influences from wall surface textures and environmental thermal loads[3]. This ambiguity leads to misjudgments or omissions in identifying minor defects, complicating the precise differentiation between genuine defects and environmental interference signals[11]. The lack of quantitative correlation between solar altitude angles, azimuth angles, and detection time windows across different latitudinal regions (e. g., equatorial versus temperate and high-latitude zones) makes thermography inspection a practical estimation rather than rigorous testing[3]. Finally, existing technologies predominantly focus on 'single-detection' scenarios, struggling to support multi-scale, high-precision monitoring and intelligent early warning throughout the entire lifecycle of external protection systems. This hinders the early intervention of defects, resulting in a generally weak monitoring-warning system.

In response to the current state of research, this paper provides a comprehensive survey on the techniques using infrared thermography to detect delamination defects on the exterior walls, concretes and other building structures. The survey aims to find out the possible way to conduct a quantitative estimation of debonded walls by single-shot thermography. However, numerous factors may affect the reliability of inspection results. To this end, this paper will trace the developmental trajectory of infrared thermography for concrete structures over the past three decades from a practical engineering application standpoint. It will systematically analyze and compare the technology's applicability, evolution of evaluation criteria, post-processing techniques, level of commercialization, engineering standards, personnel qualification requirements, and implementation conditions, thereby summarizing the key challenges that hinder the quantitative assessment of delamination defects in practical building inspections. Building on this foundation, the article will then briefly review the advancements in thermography over the last decade, with a focus on the integration and evolution of AI within passive solar thermography. Finally, it will explore the feasibility of enhancing single-frame solar infrared images through the development of a physics-constrained thermal sequence generation module. By incorporating contextual data such as acquisition time, this approach aims to reconstruct the missing temporal dimension, thus overcoming the fundamental limitations of current single-frame analysis and paving the way for quantitative defect evaluation.

2 Principles and Categories

Thermography is a vision-based nondestructive inspection technique. Like visible light inspection, thermography offers an image of objects within the field of view in the band of infrared rather than visible light. While natural-light visual inspection makes decisions based on the same knowledge that human vision uses, thermal cameras receive both reflective and emissive infrared rays from the inspected target. As a result, decision-making based on thermal images differs significantly from that based on natural-light images, let alone the limitations of camera resolution. To address the challenges of infrared thermography inspection, the type of defect is categorized, and the principles of different thermography tests are illustrated and compared.

2.1 Principle of Thermography Inspection of Wall Defects and Their Categories

Infrared thermal imaging (IRT) technology serves as the primary method for detecting internal defects within building walls. Its operational principle is rooted in Planck's law of thermal radiation: any object with a temperature above absolute zero (-273.15 ℃) emits long-wave infrared radiation within the 7-14 μm wavelength range, with radiation intensity exhibiting a positive correlation to surface temperature. Defective wall sections exhibit markedly different thermal properties compared to sound areas. For instance, the thermal

conductivity of air filling internal voids is significantly lower than that of concrete. Under thermal loading, this creates 'thermal contrast': during heating, the surface temperature of defective areas exceeds surrounding sound areas by 0.5-2 ℃, while during cooling (night-time), it falls 0.3-1 ℃ below surrounding regions. This temperature differential forms the core basis for defect localization[12]. Classified by heat source type, IRT methods are passive or active. Passive IRT utilizes solar radiation as a natural heat source, requiring no artificial heating, and is suited for large-scale outdoor inspections. For instance, in high-rise residential building facade inspections, continuous day-night thermal imaging captures temperature variations in hollow areas. Active IRT employs artificial heat sources as excitation, inducing delayed thermal responses in defect zones through brief thermal pulses to infer defect depth. This approach is better suited for laboratory precision testing or small-scale deep defect detection.

The principle of solar based thermography can be illustrated by Fig. 1[13]. Similar to active thermography, solar thermography uses sunshine as a heat stimulus outside the inspected target. Thus, the stimulus is not controllable. However, the thermal stress introduced by sunshine is strong enough to push defective areas to respond to such temperature cycles. The man-made internal voids and humidity erosion can be easily separated from raw thermal images as shown in Fig. 1.

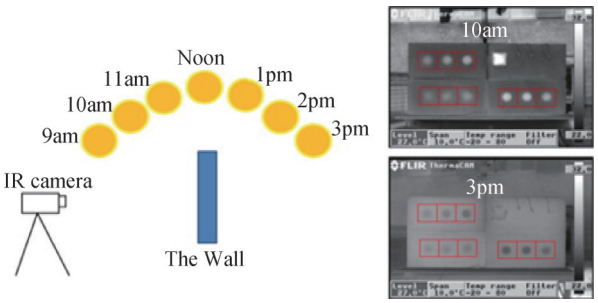


Fig.1 delamination inspection of light-mass infrastructure materials under sunlight exposure[13]

Another technique known as single-snap thermography or passive thermography is used in the practical building surveys than the solar thermography acquired a sequence of thermography. As the technique only takes one shot of thermography at one place, in the existing studies researchers treat the thermal reading in the image as emittance from the surface, although they are a combination of reflective rays and emitted ones. Therefore, the term 'Passive' is used to describe the technique. In authors' opinion, since the heat signals are still stimulated by solar radiance and changing with time, the technique should still be treated as a kind of solar thermography which suffers from lost information but keeps only one frame of data. Surely, as other data is lost, the existing post processing algorithm will not fit the data. Thus, the inspected result becomes suspectable. Such a phenomenon will be discussed in the following section.

2.2 The Development of the Techniques and Their Metrics

2.2.1 Development of the Techniques

Thermography was introduced into concrete inspection about 30 years ago[14]. The developmental trajectory of the technique is shown in Fig. 2[15]-[17]. During the first fifteen years, such inspections are mainly conducted in lab conditions due to the limitation both in the infrared camera and the post-processing algorithms. Results of outdoor tests and field tests are discussed qualitatively. However, these studies do not only demonstrate the capacity of thermography inspection in concrete delamination but also the constraints in multiple aspects, such as humidity of the concrete, daylight, winds, ambient temperature, operation time and so on. From 2015 to 2018, the number of published studies boomed in the field after Washer[18] applied time sequential features of thermal image sequence as a detection criterion. The techniques have been applied to field tests for bridges. Several factors play a more important role in the real applications compared to their roles in the lab tests: view angle[26][43], texture[43], heat flow[47], large inspection area[26] and weather conditions[48]. From 2018, a new round of mechanical studies has been conducted and the thermal image stitching techniques earlier introduced by Vaghefi[42] in 2015 have drawn the attention of researchers worldwide to build a 3D thermography model for the inspected objects. AI as well as new development detection criteria have been developed. Relative studies in the most recent 5 years have been listed in Table 1. The mainstream in the recent studies follows in the following aspects: eliminating the influence of the texture by introducing visible images[74], using photo registration techniques for multi-viewed thermal images to reduce the effect of view angles[74]-[83] and generating a model-based detection baseline to eliminate the effects of heat flow, which is influenced by the solar angle, wall orientation, the absorbance and the emittance of the inspected surface[74][83][84].

In literature, if the thermal data is acquired sequentially to make a thermal image sequence, these data can be post processed by those algorithms designed for active thermography, such as Pulse phase angle, principal component analysis, temperature signal reconstruction, restored pseudo heat flux, physically constrained machine learning (such as RPHF-EVBT) [96] and others.

Figure 3 has shown a set of thermal image sequence processed by different algorithms. However, if a single-shot passive thermography is applied, the post processing algorithm is limited except 3D thermal stitching techniques according to the existing studies.

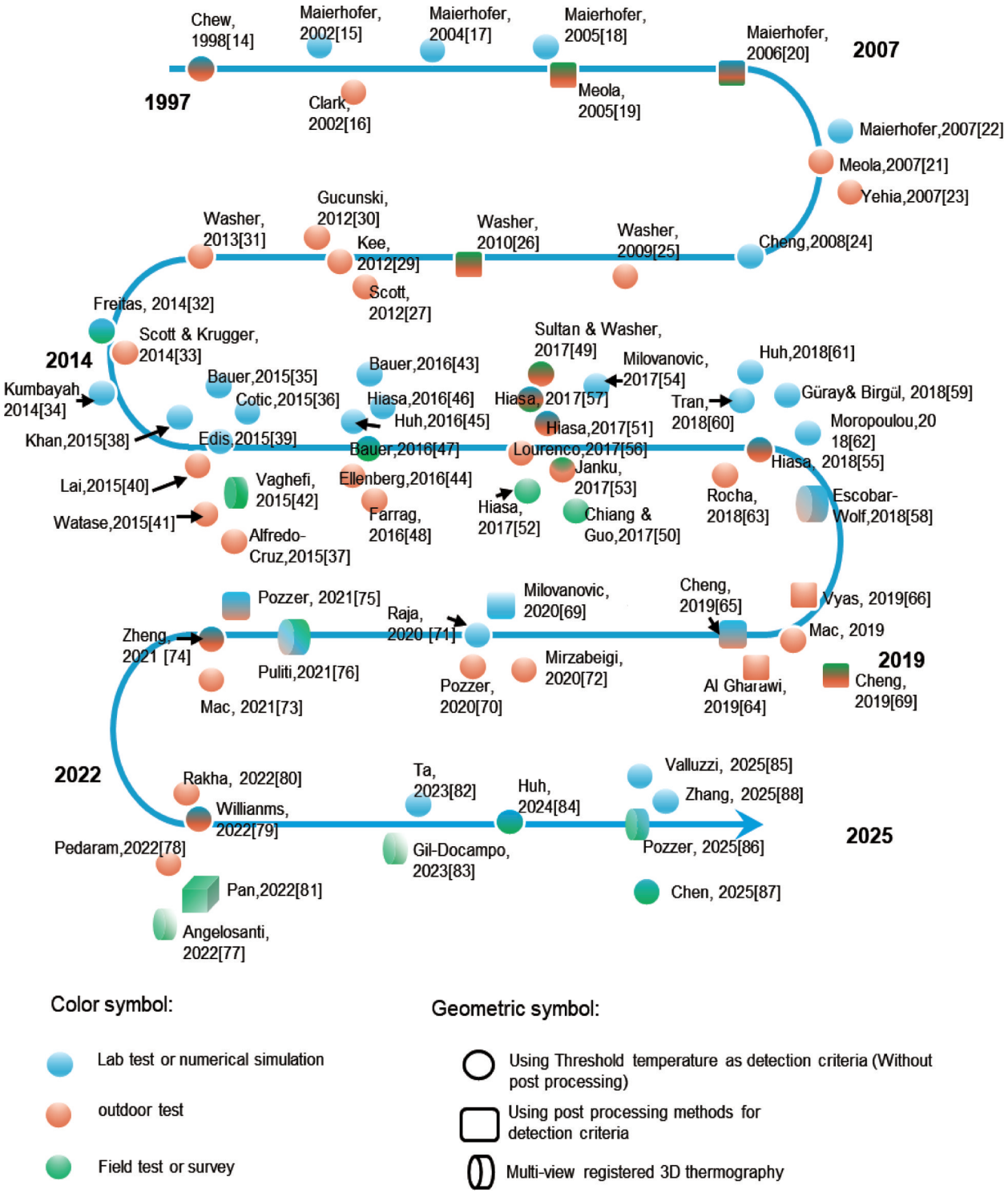


Fig.2 The developmental trajectory of thermography tests for concrete structures in the recent three decades[14-88]

2.2.2 Metrics

Thermography inspects walls and other concretes based on the thermal response as summarized in Table 1. Indeed, thermography reveals thermal anomalies directly rather than defects.

In early researches, the temperature threshold serves as the core criterion for automated defect identification and regional segmentation in infrared thermal imaging non-destructive testing, particularly for anomalies such as delamination and voids. Its fundamental function lies in quantifying the boundary between abnormal temperature fields within defective areas and intact substrates by establishing critical temperature differential values. In practical inspection scenarios, this threshold value is not constant but is modulated by the coupled effects of environmental thermal disturbances and the spatial orientation of structural components. Firstly, environmental parameters such as humidity and radiation intensity alter the extreme line levels of the surface

Table 1 Relative Studies about Thermography Inspection for Concrete Structures in Recent 5 Years

Author		year	purpose	Thermal source	test method	Criteria	inspection target
Mirzabeigi, S.[72]	Field	2022	energy assessment	inner door air	single snap	temperature anomaly	
Puliti, M. [76]	Scaled model	2021	energy auditing	solar and inner heat	multi-view-built 3D modelling at single time step	temperature anomaly	thinner wall, thermal leakage, humidity damage
Angelosanti, M. [77]	Field	2022	energy assesment, 3D thermal modeling	solar	multi-view-built 3D modelling at single time step	temperature anomaly	
Pedram M. [78]	Lab	2022	detection capacity	active	thermal image sequence	Threshold temperature Contrast	concrete void
Jesse Williams[79]	Lab & field	2022	fresco delamination	active	thermal image sequence	Threshold temperature Contrast	fresco delamination
Rakha, T[80]	Field	2022	roof proven	solar	scanning time sequence	naked eyes	water, moisture damage, thermal bridge
Chenbin Pan[81]	Field	2022	temperature anomaly separation	solar	single snap	AIM-temperature anomaly	
Quang Tai Ta [82]	Lab	2023	detection capacity in form of WTD	active	thermal image sequence	temperature contrast	concrete delamination
Mariluz Gil-Docampo [83]	Field	2023	energy assesment, 3D thermal modeling	solar	multi-view-built 3D modelling at single time step	temperature anomaly	
Huh [84]	Lab & field	2024	tunnel titles	active & Passive	single snap	temperature anomaly	rock-cut tunnels
Valluzzi[85]	Lab	2025	subsurface anomalies	active & passive	thermal image sequence	Threshold temperature Contrast	plastered masonry walls
Sandra Pozzer [86][75]	Field& lab	2025	concrete inspection	solar	multi-view-built 3D modelling at single time step		concrete delamination
Jun Chen[87]	Field& simulation	2025	wall maintenance	solar		Threshold temperature Contrast	tile delamination
Peiyi Zhang[88]	Lab	2025	earthquake assessment	active	single snap	Threshold temperature Contrast	tile delamination & deterioration

temperature field. Secondly, variations in the orientation of the target object's vertical surfaces create heterogeneous temperature gradient fields, rendering a globally uniform threshold unsuitable for meeting inspection requirements across all regions[80]. Consequently, the scientific determination of the temperature difference threshold must be grounded in environmental adaptability and regional specificity, achieving optimized detection accuracy through dynamic adjustment.

However, The thermal-physical properties of different defect types directly determine their distinct temperature difference thresholds. As stipulated in ISO 10211, defects are classified as severe thermal bridges when the temperature difference reaches ⩾8K[89]. Such defects cause localized heat flow concentration due to abrupt changes in the thermal conductivity of components, resulting in thresholds significantly higher than other defect types. The methodology for determining temperature thresholds has evolved from being 'predominantly guided by subjective experience' to being 'objectively algorithm-driven'. This progression has mitigated human interference and environmental noise, enhancing both its universality and precision[90]-[93].

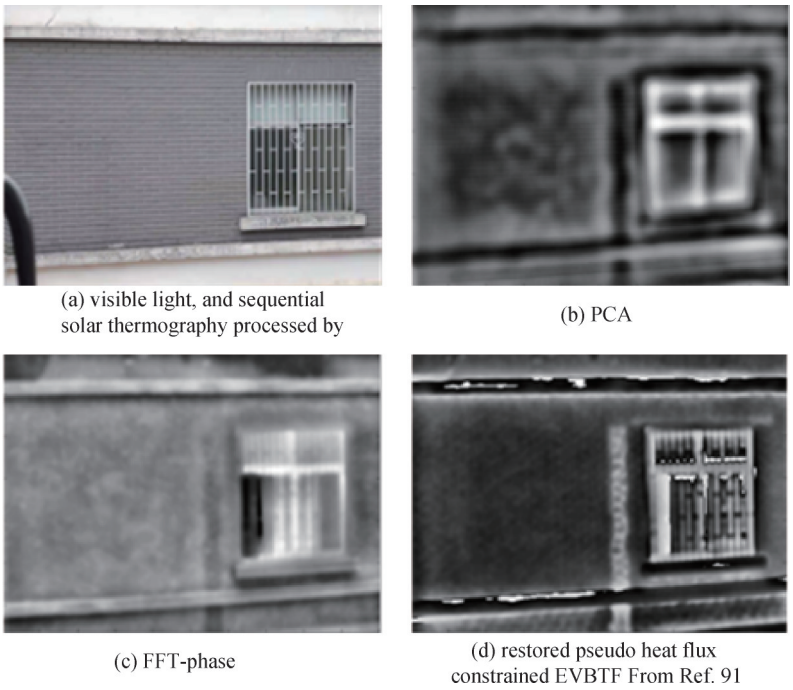


Fig.3 Photography(a) of a wall and its sequential solar thermography inspection results based on PCA(b), FFT phase(c), RPHF-EVBTF(d)[91]

The contrast-to-noise ratio serves as a pivotal metric in NDT and image processing domains for quantifying the equilibrium between defect signal discernibility and background noise interference. Its core function lies in translating signal differences between regions of interest and background into statistically quantifiable indicators, thereby objectively delineating the detectability threshold for defects amidst noise interference. CNR eliminates the influence of absolute signal intensity and noise baseline levels through normalization, enabling standardized assessment of defect discernibility across diverse inspection scenarios. It has been established as the core benchmark for evaluating signal processing technology efficacy. Higher CNR values indicate more pronounced differentiation between defect signals and background noise, thereby reducing the risks of false positives and false negatives. ISO 10880: 2017 explicitly designates 'Contrast-to-Noise Ratio' as the core parameter for evaluating thermal imaging inspection performance.[89]

Defect signals preliminarily identified by non-destructive testing techniques require multi-faceted verification for confirmation. The primary objective is to eliminate environmental interference and instrumentation errors through cross-validation. Verification methods fall into two main categories: non-destructive verification and destructive verification.

Non-destructive verification is achieved by detecting differences in the physical properties between the defect and the base material, employing methods such as the tapping test and ultrasonic rebound test. The tapping test relies on auditory distinctions between 'clear echoes' and 'dull, muffled sounds' for verification, with an accuracy rate of no less than 85%[95].

Destructive verification involves obtaining internal samples from components to visually confirm defects, though this causes localized damage. Core sampling remains the most established technique, employing specialized core drills to extract samples (≥50 mm diameter) from suspected defect areas. The cross-section of these cores is then directly examined for signs of delamination, voids, or leakage. This method has been applied in major projects such as the Hangzhou Asian Games venues, successfully identifying mortar voids 5 cm beneath tile layers with millimeter-level precision, establishing it as the 'gold standard' for defect characterization and quantification. Single-technique verification methods possess inherent limitations. With technological advancement, cross-technique combination verification approaches have emerged. For instance, the IRT + Ground Penetrating Radar (GPR) combination achieves comprehensive verification through complementary 'thermal properties - electromagnetic properties', becoming the preferred solution for complex scenarios[96].

2.3 Capacity and Constraints

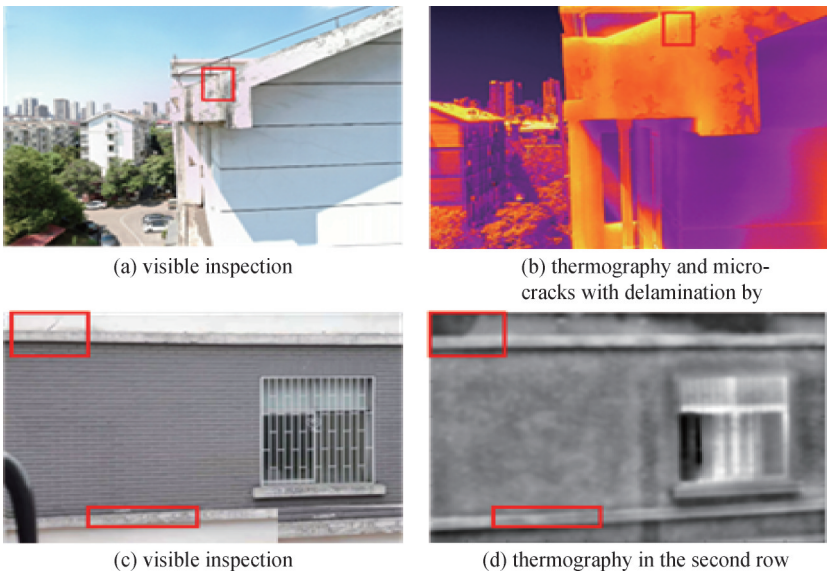
Infrared thermal imaging technology possesses irreplaceable core advantages in detecting internal wall defects. Its deep-penetration capabilities extend to revealing delamination at the concrete cover-to-reinforcement interface. Passive IRT reliably detects voids and delamination up to 80 mm deep, while active IRT combined with PPT technology can probe defects at depths exceeding 100 mm - far surpassing the penetration range of ultrasonic testing. Integration with unmanned aerial vehicle (UAV) systems significantly enhances efficiency. During exterior wall inspections of a 15-storey building, the UAV and passive IRT system completed full-

facade data collection within one day, achieving over 95% coverage. This represents 5 to 7 times the efficiency of traditional manual tapping methods without interrupting building operations. The non-contact operational mode entirely eliminates the risks associated with high-altitude climbing. Inspections of elevated walls can be conducted from ground level or low altitudes without physical contact with the wall surface, making it particularly suitable for challenging scenarios such as glass curtain walls and super-tall residential buildings.

Table 2 summarizes the detected defects by thermography based on References[73-88] and the field survey conducted by the authors from 2021 to 2025. Usually, the professionals believe that thermography will be limited in indentify surface defects, such as cracks, cladding spalling /damage, mods and decorative layer damage. However as shown in Fig. 4, the consented field survey conducted by the authors showed that thermography has the capacity to identify not only cracks, but also subsurface defects near cracks, such as the delaminations (as shown in Fig.4 b) and moisture around cracks (as shown in Fig. 4(d)). These internal defects are characterized by being 'deeply concealed yet potentially catastrophic,' with typical examples being internal voids and interfacial delamination. They are buried at a depth of 5 to 80 mm. They are barely visible but the significant difference in thermal properties between defective area and concrete provides the thermal basis for infrared thermal imaging detection[97].

Table 2 Capacity of thermography inspection for Surface Defects and Internal Defects in Building Walls

Defect Category	Typical Types	Formation Causes	Core Characteristics	Main Hazards	Visibility	Detectability
Surface Defects	Microcracks,	Thermal Stress, Adhesive Aging, External Impact, etc.	Vary with area, scale and shape; shallow depth	Bad thermal insulation ; small pieces spalling pose safety hazards, growing into delamination	Fair	Fair
	Finishing Peeling,				Good	No
	Decorative Layer loss				Good	No
	Mods				Fair	Fair
Internal Defects	Internal Void,	Inadequate Compaction, Steel Bar Corrosion, etc.	Large size, buried in depth, large difference in thermal conductivity between air inside defects and concrete	falling objects Hazard; reduced load-bearing capacity of walls; shortened service life	bad	qualitative
	Interface Delamination				bad	Qualitative
	moisture		Small size, the thermal property differences between screws and wall		No	Good
	Missing connecting screws				Very bad	Good



(a) visible inspection (b) thermography and micro-cracks with delamination by (c) visible inspection (d) thermography in the second row

Fig.4 Lab collected dataset of walls with micro-cracks (a) visible light data (b) thermal imaging data (c) cracks with delamination and (d) its thermography images

The capacity of thermography has also been limited by camera's NEDT, resolution and distance. For deep-layer delamination in concrete structures, long-wave infrared cameras are preferred with a NEDT <0.04 ℃ to

capture subtle thermal contrasts between 0.3-2.0 ℃ . When detecting hollow tiles or plaster, mid-wave infrared cameras may be employed in high-humidity environments to minimize atmospheric water vapor attenuation of infrared radiation. Optimizing environmental windows requires consideration of regional climate and building orientation.

The orientation of the wall and operation window plays an important role on detection capacity. Although infrared detection technology is widely applied and offers high detection accuracy, it still has limitations. Passive IRT detection effectiveness is highly dependent on solar radiation; in the northern hemisphere, the winter detection window for north-facing facades is only 1.5 to 2 hours. When wind speeds exceed a certain threshold, heat loss from the wall surface reduces thermal contrast, leading to the potential misdetection of shallow defects with small dimensions and depth. Southern facades in the Northern Hemisphere receive ample daily solar radiation, allowing inspection windows from 10: 00 to 14: 00 to reliably detect stratification with S/D=1.0. Northern facades with insufficient sunlight can only reliably detect defects with S/D≥2.7, necessitating extended cumulative sunlight exposure period. Winter inspections must ensure ambient temperatures exceed 5 ℃ to prevent reduced thermal conductivity and insufficient thermal contrast at low temperatures. Following the HKCI-TM1 standard, a 12-hour rainfall-free period is required prior to inspection to prevent surface heat loss from compromising temperature differentials.

Color, absorption, view angle and emissivity. The color of inspected objects does influence thermography results in two ways: first, color may change the absorption of the surface, and in the other way it may change the emissivity of the surface. However, the exact relationship between the color and the absorptiveness in the infrared band has been left miserly (as shown in Fig. 5): a black tile does absorb more infrared rays than a white one, there is no guarantee that the darker ones absorb more than the lighter ones. The researchers from The Hong Kong Polytechnic University[98] have conducted an experiment about the effect of color on the thermography by making a tile sample with 8 different colors. By monitoring their temperature changes a day long, it can be seen that the black one absorbs and emits most infrared waves, the white one the least. The lighter gray one absorbs less than the darker gray, but it emits almost the same as the darker one since the temperature of the two regions appears almost the same. As a result, in the real field inspection, a patterned tile design makes a thermography inspection based on thermal anomaly superficial.

The same temperature has different readings in thermography taken under different tilt angles. For example, Hong Kong's HKCI-TM1[99] mandates an inspection angle ⩽40° , whereas Singapore's TR 119: 2024[100] permits ⩽60° . When applying differing

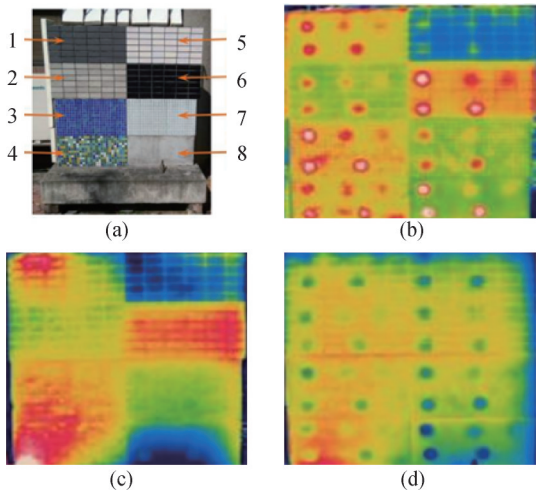


Fig.5 The effect of colorization on infrared absorptance and emittance a) photograph of the tested sample, the thermal images at b) 11:00am, c)15:00 and d)20:00[98], details about the tiles labeled in a) can be found in the Ref. 98

standards to the same transnational project, defect identification consistency ranges between 70% and 80%, necessitating additional parameter calibration.

Furthermore, equipment and operational costs remain high. Professional thermal imagers with resolutions exceeding 640×480 pixels cost 5-10 times that of visible-light cameras. Accompanying signal processing software further increases initial investment and ongoing maintenance expenses, limiting suitability for small-to-medium projects.

3 Testing Standards and Evaluation Criteria

3.1 Commercialization & Industrial institutions

In China, multiple enterprises have successfully implemented and scaled relevant technologies for practical application. For instance, Ningbo Hanhua Inspection in Zhejiang employs a collaborative operation model integrating "drone-based infrared scanning with wall-climbing robotic precision detection," which enables rapid scanning of exterior walls on 16-story high-rise buildings within five minutes. This approach has been deployed across multiple residential complexes in Ningbo. In Shanghai, Weixiu Building Maintenance has introduced the "WallGuard" intelligent drone inspection system, which combines infrared thermal imaging and AI. Reported to improve inspection efficiency by over 80%, the system is primarily used to identify defects such as water leakage and voids in exterior walls and roofs. Similarly, the Taihang Company of Huayang Group in Shanxi utilizes drones equipped with high-definition and infrared sensors to enable full-process dynamic monitoring in commercial rooftop illumination projects, achieving a detection accuracy rate of 98%. These cases illustrate the strong localized implementation capabilities

of Chinese firms in technology integration and engineering applications.

In North America, companies such as U. S. -based Lamarr.AI have taken a leading role by deeply integrating AI, drones, and thermal imaging to enable autonomous diagnosis of building envelope defects. Beyond quantifying building energy loss and supporting significant cost savings for owners, the company has attracted positive attention in capital markets, having secured over USD 1 million in funding. This reflects investor confidence in its technological approach and commercial prospects. European companies also demonstrate distinctive technological expertise in this field. Italy's DarkWave Thermo specializes in building façade diagnosis using high-resolution infrared thermal cameras, with particular proficiency in detecting tile delamination and coating defects. The company frequently serves historical preservation projects and forensic investigations. Germany's Lumoview employs patented 360-degree infrared and panoramic cameras to rapidly generate 3D thermal performance models of buildings. Its user-friendly operation and immediate results have been recognized through industry startup awards.

In other regions of Asia, South Korea's HomeCheck integrates digital diagnostic technologies such as infrared detection with expert manual assessment to perform data-driven inspections on more than 30,000 homes annually. The company is expanding from inspection services toward a comprehensive building lifecycle data platform. Singapore's Screening Eagle supports building maintenance through integrated sensor arrays and software platforms, providing systematic data solutions. As a technology firm originating from Singapore, it has gained international attention for its innovative model, which contributes to digital transformation in the building inspection industry. Hong Kong's RaSpect has developed an intelligent inspection system that combines drones, infrared imaging, and AI, designed for post-construction exterior wall assessment to effectively identify cracks and water leakage. Given Hong Kong's status as an international financial and technological hub, such companies often benefit from stronger access to capital, facilitating venture funding and project financing that drive technological iteration and market expansion.

Overall, the field of wall and roof void detection has entered an intelligent development phase characterized by multi-technology integration. Drones, infrared thermal imaging, and artificial intelligence have become common frameworks within the industry. Enterprises across different regions have developed distinct technical pathways and application models adapted to local market and regulatory conditions. In terms of financing, particularly in regions such as North America, Singapore, and Hong Kong, dynamic innovation ecosystems have enabled relevant companies to secure capital more readily. This not only accelerates technology R&D and product refinement but also supports rapid business model replication and international growth. Looking forward, as detection accuracy and data analytic capabilities continue to advance, this technology is poised to play an increasingly central role in building safety monitoring, energy efficiency management, and maintenance decision-support systems.

3.2 Core Inspection Standards

With the widespread adoption of infrared thermal imaging technology in building safety inspections, international organizations and various regions have progressively introduced and refined standards for thermal imaging building assessments. We have collated regional inspection standards in Table 3, analyzing their similarities and differences across three dimensions: equipment configuration specifications, environmental requirements for inspections, and reporting protocols.

Table 3 demonstrates that regional inspection standards are grounded in international benchmarks, with adjustments made to accommodate local geographical and climatic characteristics. This complementary system of variations facilitates the global application of infrared thermal imaging technology in building inspections. This research provides a reference framework for cross-regional inspection activities, thereby mitigating potential disputes arising from differing inspection standards.

3.3 Personnel Qualification Requirements

Inspection standards vary across different regions, and differing standards impose distinct requirements on personnel qualifications. We shall analyze the personnel qualification requirements stipulated in various inspection standards, with specific details presented in Table 4.

This table compares the personnel qualification requirements for Infrared Thermography (IRT) in building facade inspections under various international and regional standards. The ISO 9712 certification scheme forms the common core, with Level 1 typically authorizing equipment operation and Level 2 qualifying personnel for independent image analysis and defect diagnosis. Beyond this foundation, several standards impose stricter, multi-layered criteria. These include mandates for periodic recertification and continuous training (e. g., Singapore), formal registration with authorities, and alternative qualification pathways combining local training with extensive experience (e.g., Hong Kong). Crucially, senior roles such as report authors are consistently required to possess integrated expertise, merging thermographic analysis with building physics knowledge to provide contextual diagnostics and remediation advice. Collectively, these frameworks ensure inspectors possess both technical proficiency and the necessary contextual understanding for reliable assessments[106]

Table 3 Standards of thermography inspection for Surface Defects and Internal Defects in Building Walls

Standard	Equipment Configuration Specifications				Testing Environment Requirements					Preparation of Test Reports
	Spatial resolution	NEDT	Spectrum	Others	Environment Requirements	Wetness	Wind speed	ΔT	Others	
GB/T 45166-2024[101]	>= 1.2 mrad	⩽ 0.03 ℃			Temperature -10 ℃ ~ 50 ℃	Relative Humidity < 85%	< 2 m/s shielded			Includes nine key elements: specimen information, inspection equipment parameters, thermal image sequences, defect rating conclusions, etc. The measurement error for defect dimensions within ±5%. The retention period for raw data >= ten years.
D4788-03R22[102]		⩽ 0.1 ℃	8-14 μm	calibrated	continuous direct sunlight	dry surface	⩽6.5m/s	⩾10 ℃	Deepness:<4 inches / 100mm	-
ISO 6781-1:2023[103]	⩽1.5×10^{-3} rad	⩽0.1 ℃ (at 30 ℃)	8-14 μm	calibrated						Includes 'thermal image + visible light reference image + quantitative defect description' (e.g. defect area, estimated depth from surface), clearly indicating defect severity level (minor / moderate / severe).
HKCI TM1:2022[99]	⩽ 1.3 mrad	⩽ 100 mK (at 25 ℃)	7-14 μm		Clear Sky ⩾12 consecutive hours	wall moisture content ⩽ 15%	⩽6.5 m/s		Operation window chosen based on orientation	Includes 'Building Information - Environmental Parameters - Equipment Calibration Records - Defect Classification Table - Thermal Imagery and Visible Light Comparison Images'
JGJ/T 277-2012[104]	⩽1.5 mrad	⩽0.1 ℃ (at 25 ℃)	7-14 μm		Ambient temperature 5-35 ℃	completely dry external wall	: ⩽5 m/s	⩾5 ℃		Includes 'Cover Page - Table of Contents - Project Overview - Testing Basis - Instrument Information - Test Results - Conclusions and Recommendations - Appendix'
Regulations on Periodic Inspection of Buildings and Building Facades in Singapore 2021[105]					temperature 25-35 ℃	Relative Humidity ⩽ 75%	⩽ 5 m/s	⩾ 5 ℃		The report must be signed by a Competent Person approved by the Building Control Authority (BCA) and submitted to the BCA system for record-keeping.

Table 4 Personnel Qualification Requirements under Different Inspection Standards

Standard	Personnel Qualification Requirements
GB/T 45166-2024[101]	Holds ISO 9712 certification, having passed specialized training and assessment prior to fieldwork, possessing theoretical knowledge of heat transfer and image analysis capabilities.
ISO 6781-1:2023[103]	Equipment Operator: Must hold ISO 9712 Level 1 infrared inspection certification, proficient in equipment operation and fundamental environmental control. Image Analyst: Must hold ISO 9712 Level 2 certification, capable of identifying interference from complex backgrounds (e.g., shadows, reflections) and accurately determining defect types. Report Author: Must possess building thermal engineering knowledge (e. g., familiarity with ISO 10211 thermal bridge calculations), able to integrate infrared findings with building structures and formulate remediation recommendations.
HKCI TM1:2022[99]	Report Signatory: Must satisfy either of the following criteria: 1. Hold an internationally recognized Level 2 infrared thermography qualification (e.g. ASNT Level 2, ISO 9712 Level 2) + 4 years of laboratory technical/management experience (including 2 years of IRT inspection); 2. Complete IRT training from a Hong Kong-accredited institution (e.g. The Hong Kong Polytechnic University course, Appendix C) + 4 years of experience (including 2 years of IRT); Inspection Operator: Must meet one of the following criteria: 1. Hold Level 1 certification (e.g., ASNT Level 1) + 1 year of hands-on IRT experience. 2. Complete local Hong Kong IRT training (e. g., HKCI-accredited course) + 1 year of hands-on experience. 3. Hold an advanced certificate in a relevant field (e.g., Higher Diploma in Civil Engineering) + 6 years of direct IRT technical/management experience.
JGJ/T 277-2012[104]	Inspectors must undergo specialized technical training to master the operation of infrared thermal imaging cameras, the interpretation of thermal images, and knowledge of external wall construction.
Building Control (Periodic Inspection of Buildings and Building Facades) Regulations 2021[105]	Personnel Qualifications: ISO 9712 Level 2 Certification Infrared thermal imaging inspectors must possess internationally recognized qualifications and comply with Singapore's local certification requirements: Qualification Level: To independently operate IRT equipment and interpret thermal images, personnel must hold ISO 9712 Level 2 or higher certification in 'Non-Destructive Testing - Qualification and Certification of Personnel', with the qualification explicitly stating 'Infrared Thermal Imaging (IRT)' as the inspection method. Qualification Maintenance: Certified personnel must undergo recertification every 3-5 years (including theoretical assessment and practical verification) and complete a BCA-approved 'NDT Technical Update Course' (e.g., annual training of no fewer than 8 hours on new IRT methodologies). Institutional Registration: Inspection agencies must submit personnel qualification records to the Building and Construction Authority (BCA) for registration. Personnel without such registration may not participate in statutory facade inspection projects.

4 Advances in Machine Learning & its Potential application

4.1 Intelligent Defect Characterization and Distribution

Traditional methods for detecting defects in building facades primarily rely on visual assessment and mechanical tapping. Their accuracy is constrained by both the inspector's experience and environmental interference, leading to significant subjective bias and a high likelihood of overlooking small-scale defects. The introduction of deep learning algorithms has overcome the limitations of manual inspection, enabling precise and standardized defect identification. The core technical approach employs a Convolutional Neural Network (CNN) as its foundational architecture. Through multimodal data input (visible light and infrared thermal imaging) and model optimization, it achieves automated defect classification and localization.

For concurrent identification of heterogeneous defects (e. g., cracks + hollow voids), the 'Multimodal Intelligent Defect Recognition System' developed jointly by Shenzhen Ruijie Engineering Consulting Co., Ltd. and the Hong Kong University of Science and Technology employs feature-level fusion of visible light texture and infrared temperature field data to construct a dual-branch CNN model. During field testing at China Mobile's Beijing campus (28-storey office building), this system elevated the defect detection rate from 61% achieved manually to 93%, while maintaining a false detection rate below 7%. Single-pass inspection efficiency surpassed manual methods by a factor of five[107][108].

4.2 3D Pointing Registration Thermography for BIM

Traditional processing of the vast data generated by building exterior wall safety inspections requires manual

frame-by-frame interpretation, making temporal comparative analysis difficult to achieve. AI technology, however, establishes a comprehensive analytical framework encompassing 'pre-processing-feature extraction - dynamic modelling' to enable efficient data transformation and value extraction.[109]

The 'Building Exterior Wall Defect Dynamic Monitoring Cloud Platform' developed by Guangxi Academy[110] of Building Research employs temporal data comparison algorithms to calculate differential values for defect parameters across different inspection cycles, generating defect expansion rate curves. The platform supports real-time cloud data transmission and automated report generation. Utilizing NLP (Natural Language Processing) technology, it converts inspection data into safety assessment reports compliant with the Technical Standards for Building Structure Inspection. This reduces report generation time from 24 hours manually to just 1.5 hours per report[110].

Traditional methods for locating defects on complex building facades rely on manual marking and cross-referencing with drawings, which suffer from significant spatial coordinate deviations and difficulties in assessing overall risk. AI technology integrates oblique photography, BIM (Building Information Modelling), and 3D point cloud processing to establish a 'defect-space-model' associative mapping, enabling visualization and traceability of inspection results[111].

To achieve precise defect-to-3D-model matching, Li et al. proposed a 'feature point matching-based defect coordinate mapping algorithm'. This converts AI-detected defect pixel coordinates into world coordinates via SIFT feature extraction, subsequently embedding them into the BIM model. During field testing at Shanghai's Bank of Communications Financial Tower (265 meters tall), this technology enabled three-dimensional visual annotation of 35 defect categories (including glass fogging and component corrosion). Managers could examine spatial distributions by sectioning and rotating the model, achieving a fourfold improvement in information transmission efficiency compared to traditional two-dimensional drawings[111][112].

4.3 Dataset Generation Based on Artificial Intelligence

In the fields of industrial quality inspection and automated production, high-quality and diverse visible-light image data serve as the foundation for training robust visual models. AI-generated data technology, leveraging generative network models such as Generative Adversarial Networks (GANs) and diffusion models, produces highly realistic images of defects in industrial products, effectively expanding and enhancing training datasets. This significantly improves the generalization capability and recognition accuracy of downstream detection models in unseen scenarios, thereby addressing the challenges of scarce defect samples and the high cost of real data collection. Currently, AI-generated data technology has been widely applied to resolve the "long-tailed distribution" of scarce data, simulate images from hazardous environments or extreme operating conditions, and serve as an efficient data augmentation tool to enhance model robustness.

With the advancement of industrial intelligence, there is an increasing demand for greater diversity and authenticity in synthetic data, driving continuous evolution in related research. A mainstream direction involves improving the architecture of generative models or optimizing training strategies to enhance image quality. For example, Wei et al. [113] proposed a data augmentation method in a transformed feature space, which disentangles features to identify directions associated with diversity, thereby generating images beyond the original sample distribution and achieving controllable enhancement of defect features. Meanwhile, against the backdrop of breakthroughs in language models, cross-modal controllable generation techniques have also attracted widespread attention. For instance, Sun et al. [114] introduced the AnomalyAny framework, which utilizes GPT-4 to automatically generate detailed anomaly descriptions, increasing the diversity of anomalies. During inference, Stable Diffusion is employed to directly generate complex defects that meet industrial standards. Such research enables the generation of images for specific industrial scenes based on textual descriptions or sketch instructions, further enhancing the flexibility and targeted applicability of data generation.

AI-generated data technology has also been widely applied in specialized imaging domains such as remote sensing and medical imaging, effectively alleviating challenges related to difficult data acquisition, high annotation costs, and privacy sensitivity. In the field of remote sensing, generative models are employed to create multi-scale, high-resolution satellite imagery to support tasks such as land classification and disaster monitoring. The MetaEarth framework, proposed by Yu et al. [115], successfully achieves the generation of seamless, visually continuous remote sensing images for any global location and at multiple resolutions. This is accomplished through a resolution-guided self-cascading generation framework combined with an innovative sliding-window generation method and a noise sampling strategy. In medical imaging, the general Medical Image-Natural language generation model, MINIM, introduced by Wang et al. [116] can synthesize medical images (e.g., CT, X-ray, MRI) of different organs based on textual instructions. It effectively augments existing datasets and significantly improves the classification accuracy for tasks such as EGFR mutation detection in lung cancer and HER2 mutation detection in breast cancer, demonstrating considerable potential as a General Medical Artificial Intelligence (GMAI). Furthermore, in non-destructive testing, Meng et al.[117] employed a GAN integrated with a coordinate attention module to effectively suppress

various artifacts—such as noise, blur, and white spots—in real neutron imaging. The common rationale behind these applications lies in leveraging generation technology to overcome the inherent constraints of real-world data acquisition, thereby providing near-limitless and secure training resources for domain-specific models and unlocking deeper analytical potential.

Leveraging style transfer techniques in AI generation to convert vast amounts of visible-light images into infrared data serves as an effective approach to addressing the scarcity of infrared datasets. Current mainstream methods primarily focus on two core objectives: semantic preservation and stylistic adaptation. Techniques such as CUT[118] are employed to constrain semantic consistency during image translation, while GANs are used to ensure the visual style closely aligns with that of real infrared data. Against the backdrop where strategies like attention mechanisms and multi-scale processing have been extensively studied, some research has begun to explore frequency-domain features within images. For instance, Wang et al.[119] proposed MappingFormer, which incorporates dedicated modules in the generator to separately process high-frequency details and low-frequency structural information of images, and introduces contrastive learning to reinforce consistency constraints in cross-modal mapping. This approach has achieved significant performance improvements on datasets such as AVIID-1 and IRVI. However, such techniques still face the challenge of insufficient physical consistency. Since visible-light images inherently lack thermal information, GAN-based methods often produce images that are "visually plausible but physically incorrect, " particularly in scenarios involving domain shifts due to seasonal variations, weather conditions, or sensor differences. In such cases, key thermal features of target objects in the generated images are prone to blurring or distortion, thereby undermining the generalization capability of downstream models in real infrared scenarios. To address the issue of thermal feature distortion in image translation, Li et al.[120] proposed the ThermalMask framework, which utilizes an SMGN module to infer potential thermal signals from visible-light images and applies pixel-spectrum dual constraints to enhance edge clarity and physical plausibility in the generated targets. This advancement propels the translation from visible light to infrared from "morphological imitation" toward "physical-semantic consistency."

4.4 Physical Law Constrained Machine Learning

Inverse models for active infrared thermal imaging primarily encompass physics-driven and data-driven approaches. Physics-based models are often constrained by the complexity of real-world applications and model simplifications, with their performance highly sensitive to boundary conditions and noise. Conversely, while traditional data-driven methods like Gaussian Process Regression[121], Random Forest Regression[122], and standard Neural Networks[123] can extract statistical features from thermal images, their effectiveness is notably limited under small-sample conditions typical in infrared non-destructive testing, which is often characterized by sparse data, high noise, and weak signals.

Given these challenges, Physics-Informed Neural Networks (PINNs) present a compelling candidate as a baseline model for this domain. By integrating physical laws (e.g., the heat conduction equation) directly into the learning process, PINNs achieve a synergistic physics-data dual-driven learning paradigm. This inherent regularization by physics enhances robustness against data sparsity and noise compared to purely data-driven supervised methods. Studies have demonstrated PINNs' potential in solving 2D steady-state and transient heat conduction problems[124]-[126] with promising extensions to 3D applications and defect detection. For instance, Shukla et al.[128] successfully employed a PINN framework to reconstruct defect distributions from ultrasonic data, highlighting its adaptability for inverse identification tasks. Although challenges remain—such as convergence stability with high-frequency components and the need for tailored Fourier feature embeddings for parabolic equations like heat conduction[128]—the foundational architecture and proven applicability of PINNs in related thermal and defect identification problems establish a strong rationale for their adoption as a baseline in infrared thermographic inversion.

At its core, thermography detection of defects in complex structures is an inverse problem: it seeks to predict the internal physical parameters of a subject from its surface temperature measurements and structural information. By extracting variation from a temporal sequence lasting a day or longer, several factors such as orientation of the wall can be eliminated. However, in industrial practice, the inspection usually relies on single-snap thermography to balance efficiency and effect. This method can be treated as a thermal image sequence with all the other frames lost if the critical snapshot is taken within the operation windows. By such a method, a physically constrained machine learning model may help the method reliably and quantitatively identify defective areas from the healthy one.

A review of conventional inversion theories shows that physics-driven models chiefly circumvent the "curse of dimensionality" by imposing two types of constraints: assumptions about the physical process itself and assumptions about the boundary conditions. The efficacy of these models is therefore highly sensitive to the validity of these assumptions; inappropriate or distorted constraints can lead to inversion failure and fundamentally limit detection performance. In contrast, data-driven models eschew the need for mechanistic knowledge, instead tackling dimensionality through

sparsity or statistical distribution priors. Yet, this approach introduces its own limitations. Both supervised and unsupervised data-driven models exhibit an excessive dependence on the statistical characteristics of the training data, which critically hampers their performance on small-sample defect detection. Furthermore, they are fundamentally incapable of directly addressing chaotic physical phenomena like bifurcation.

Physics-Informed Neural Networks (PINNs) emerge as a powerful alternative by embedding physical laws directly into the neural network. This hybrid approach leverages the capacity of deep networks to handle high-dimensional problems, a key weakness of purely physics-based methods. Simultaneously, by encoding physical principles as constraints, PINNs mitigate the overfitting and data dependency issues that plague traditional data-driven models, thereby drastically reducing the demand for large datasets. This integration provides a novel and promising direction for advancing inversion models in infrared thermography. For example, with a physical law constrained machine learning, it is possible to extract features of deeply buried foreign objects from soils (Data and image are provided by Dr. Vavilov in Tomsmak University and reproduced by the authors). It can be observed from Fig. 6(d), which is generated using a physically constrained machine learning algorithm based on single-shot thermography, that the deeply buried artificial foreign objects are more clearly visible than in the raw thermal image (Fig. 6(c)), although the result is weaker than that obtained using RPHF-EVBTF (Fig. 6(b)).

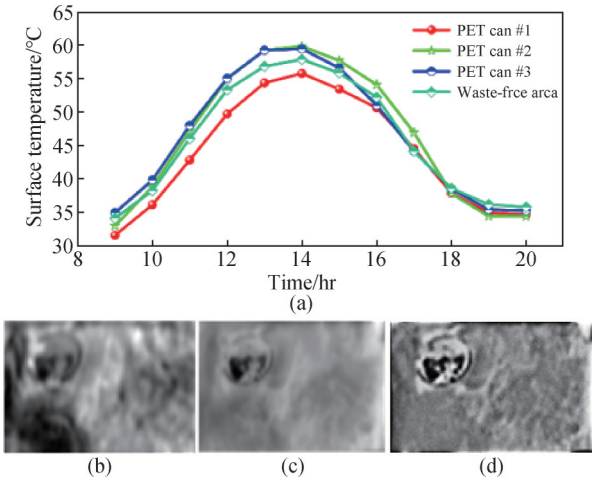


Fig. 6 Buried foreign objects in soil by solar thermography a) operating windows of Buried foreign objects in soil[129], b) the pseudo heat flux estimated by RPHF-EVBTF result at 9:50[129], c) raw thermal image at 9:50[129]; d) reproduced results by single-snap RPHF-EVBTF of c).

5 Conclusions

The application of infrared thermography in building inspection has matured into a substantial market, particularly in international contexts, supported by a series of established practical standards and a set of existing research. However, this review highlights a critical technological bottleneck: conventional, single-frame passive solar thermography remains incapable of the quantitative detection of exterior wall delamination. While active thermography, with its controllable heat source, can successfully analyze the contrast between thermal response and heat excitation to pinpoint a defect's location and depth, its passive counterpart is fundamentally hampered in field applications. The core issue is the loss of the temporal evolution of the thermal response in single-frame analysis. This loss renders the advanced analytical methods of active thermography inapplicable, creating a significant gap where, despite early research emphasizing the crucial role of surface heat flux dynamics, this knowledge cannot be leveraged in practice.

Consequently, the field has defaulted to using static temperature anomalies as the primary detection criterion, an approach fraught with limitations. This method cannot reliably distinguish between previously repaired wall sections and actual delamination, as both manifest as thermal irregularities. Furthermore, the correlation between temperature anomalies and subsurface defects is severely weakened by the non-linear influence of wall color on surface absorptivity and emissivity. Compounding these issues, confounding factors such as wall patches and shadows create thermal anomalies that are virtually indistinguishable from those caused by structural defects in a single infrared image, leading to high rates of false positives and unreliable diagnostics.

Looking ahead, the convergence of Artificial Intelligence (AI) and 3D vision modeling technologies heralds a new paradigm for wall delamination detection, offering tangible solutions to these long-standing challenges. On one hand, reconstructing the building's surface temperature distribution as a 3D model promises to enhance thermal contrast between different regions, making subtle defects more pronounced. On the other hand, the fusion of thermal data with co-registered visible light textures provides a powerful mechanism to differentiate the source of a thermal anomaly: determining whether it originates from a surface property change (e. g., color, texture) or an internal structural change (e.g., delamination).

In this context, the development of Physics-Informed Neural Networks (PINNs) is particularly promising. PINNs offer a sophisticated framework to fuse multimodal data, including visual imagery, 3D models, and acquisition timestamps, while embedding the underlying physics of heat transfer. This enables the creation of a highly realistic, physics-based detection benchmark. Critically, by feeding this rich, contextual information into generative models, it becomes possible to reconstruct or "hallucinate" the missing thermal response time-series data. This breakthrough would bridge the gap between passive and active thermography,

transforming passive inspection from a qualitative screening tool into a rapid, on-site, and quantitative diagnostic technique, thereby fulfilling its potential for reliable and definitive assessment of building integrity.

Author Contribution:

Dr. Yibin He has been responsible for conceptualization; funding acquisition; Project administration; Resources; review and editing. Zhengrong Yuan conducted the field survey and the experiment, analyzed the literature, and did most of the writing. Bo Yang has analyzed the field survey data, drawn the figures and tables, and edited and reviewed the manuscript. Hongxin Xia has supervised the project and assisted in organizing and analyzing the patents and the standards. Wei Qiu has worked on the software writing for Fig. 6(d), figure-drawings, editing and reviewing.

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Data Availability:

Not applicable. This study is mainly a review of existing literature. The unpublished original data are available from the corresponding author on reasonable request.

Conflicts of Interest:

The authors declare no competing interests.

References

[1] Liang X. D., Liu F., et al. (**2025**). Safety management and quality control technology in the construction of high-rise building facades [In Chinese]. [J] *China Construction Metal Structure* , 24(18): 151-153. doi: 10.20080/j. cnki. ISSN1671-3362.**2025**.18.051.

[2] Oh T., Kee S.H., et al. (**2013**). Comparison of NDT methods for assessment of a concrete bridge deck. [J] *Journal of Engineering Mechanics* , 139(3): 305-314. doi: 10.1061/(ASCE)EM.1943-7889.0000441

[3] Pozzer S., Omidi Z., et al., (**2024**). Passive infrared thermography for subsurface delamination detection in concrete infrastructure: Capabilities. [J]*Construction and Building Materials* , Volume 494, 143177, doi: 10.1016/j.conbuildmat.2025.143177.

[4] Zhu B., Zhang H.,(**2014**). Study on the occurrence probability of falling risk of external wall facing bricks in high-rise buildings based on Bayesian network [In Chinese][J]. *Journal of China Three Gorges University (Natural Sciences)* , 36(4): 83-86. doi:10.13393/j.cnki.issn.1672-948X.2014.04.018.

[5] Chengdu municipal commission of urban and rural development, Chengdu Municipal Bureau of Urban Planning (**2018**). "Notice on strengthening the use and management of external wall facing bricks adopting external thermal insulation form [In Chinese]. " [Online]. 15 October **2018**; URL not provided.

[6] Ministry of housing and urban-rural development of the people's republic of china (MOHURD), n. d. Announcement on issuing the 'First batch of eliminated catalogues of construction technologies, Equipment and materials endangering production safety in housing construction and municipal infrastructure projects' [In Chinese].*[Online]* , URL not provided.

[7] Shao Z.J. (**2019**). An infrared detection method for hollowing of external wall facing bricks [In Chinese][D]. *Thesis, Dalian University of Technology* , Dalian, China.

[8] Zhang Y., Li N. (**2019**). Current status, problems and preventive measures of sealing and waterproofing technology for building external windows in China [In Chinese] [J]. *China Building Waterproofing* , S2: 1-4, 13. doi: 10.15901/j.cnki.1007-497x.**2019**.S2.001.

[9] Gao S.D. (**2022**). Causes and prevention countermeasures of external wall leakage in high-rise buildings [In Chinese] [J]. *Foshan Ceramics* , 32(11): 77-79.

[10] Pozzer S., Ramos G., et al. (**2024**). Enhancing concrete defect segmentation using multimodal data and Siamese Neural Networks[J]. Automation in Construction, Volume 166., 105594, doi: 10.1016/j.autcon.**2024**.105594.

[11] *BS EN* 13187, 1999. Thermal performance of buildings—qualitative detection of thermal irregularities in building envelopes—infrared method. British Standards Institute, London, UK.

[12] Xie J., Wu C. et al. (**2021**). Detection of internal defects in CFRP strengthened steel structures using eddy current pulsed thermography[J]. *Construction and Building Materials* , Volume 282, 122642, doi: 10.1016/j.conbuildmat.2021.122642.

[13] Martin M., et al. (**2022**). Infrared thermography in the built environment: a multi-scale review[J]. *Renewable and Sustainable Energy Reviews, Volume* 165, 112540, doi: 10.1016/j.rser.**2022**.112540.

[14] Chew M. (**1998**). Assessing building façades using infra-Red thermography. *Struct. Surv* .16, 81-86.

[15] Maierhofer C., Brink A., et al. (**2002**) Transient thermography for structural investigation of concrete and composites in the near surface region[J]. *Infrared Physics & Technology* , Volume 43, Issues 3-5, Pages 271-278, doi: 10.1016/S1350-4495 (02)00151-2.

[16] Clark M. R.; McCann D. M.; Forde M. C. Application of Infrared Thermography to the Non-Destructive Testing of Concrete and Masonry Bridges. *NDT E Int.* **2003**, 36, 265-275.

[17] Maierhofer C., Wiggenhauser H., et al. (**2004**) Quantitative numerical analysis of transient IR-experiments on buildings [J], *Infrared Physics & Technology* , Volume 46, Issues 1-2, 2004, Pages 173-180, doi:10.1016/j.infrared.2004.03.022.

[18] Maierhofer C., Brink A., et al. (**2005**) Quantitative impulse-thermography as non-destructive testing method in civil engineering—experimental results and numerical simulations [J]. *Construction and Building Materials* , Volume 19, Issue

10, Pages 731-737,doi: 10.1016/j.conbuildmat.2005.06.002.

[19] Meola C., Di Maio, et al. (**2005**) Application of infrared thermography and geophysical methods for defect detection in architectural structures[J]. *Engineering Failure Analysis*, Volume 12, Issue 6, Pages 875-892, doi: 10.1016/j. engfailanal. 2004.12.030..

[20] Maierhofer C., Arndt R., et al. (**2006**) Application of impulse-thermography for non-destructive assessment of concrete structures[J]. *Cement and Concrete Composites* , Volume 28, Issue 4, Pages 393-401, doi: 10.1016/j.cemconcomp.2006.02.011.

[21] Meola, C.(**2007**) Infrared thermography of masonry structures [J]. *Infrared Physics & Technology* , Volume 49, Issue 3, Pages 228-233, doi:10.1016/j.infrared.2006.06.010.

[22] Maierhofer C., Arndt R., et al. (**2007**) Influence of concrete properties on the detection of voids with impulse-thermography[J]. *Infrared Physics & Technology* , 49, 213-217, doi: 10.1016/j.infrared.2006.06.007.

[23] Yehia S., Abudayyeh O., et al. (**2007**) Detection of Common Defects in Concrete Bridge Decks Using Nondestructive Evaluation Techniques[J]. *Journal of Bridge Engineering* . 12, 215-225.

[24] Cheng C., Cheng T., et al. (**2008**) Defect detection of concrete structures using both infrared thermography and elastic waves [J]. *Automation in Construction* , Volume 18, Issue 1, Pages 87-92, doi :10.1016/j.autcon.2008.05.004.

[25] Washer G., Fenwick R., et al. (**2009**) Effects of Environmental variables on infrared imaging of subsurface features of concrete bridges[J]. *Transportation Research Record.* 2108. 107-114. doi: 10.3141/2108-12.

[26] Washer G., Bolleni N., et al. (**2010**) Thermographic imaging of subsurface deterioration in concrete bridges[J]. *Transportation Research Record: Journal of the Transportation Research Board* , 2201, 27-33, doi: 10.3141/2201-04.

[27] Scott M., Luttig H., et al. (**2012**) Passive infrared thermography as a diagnostic tool in civil engineering structural material health monitoring[J]. *Rehabilitation and Retrofitting* ,760-765.

[28] National Academies of Sciences, Engineering, and Medicine. Nondestructive Testing to Identify Concrete Bridge Deck Deterioration, (**2012**) *The National Academies Press: Washington*, DC, USA.

[29] Kee S. -H., Oh T., et al. (**2012**) Nondestructive bridge deck testing with air-coupled impact-echo and infrared thermography[J]. *Journal of Bridge Engineering* , 17. doi: 10.1061/(ASCE)BE.1943-5592.0000350.

[30] Gucunski N., Imani A., et al. (**2013**). Nondestructive testing to identify concrete bridge deck deterioration. *Shrp Report* .

[31] Washer G., Fenwick R., et al. (**2013**) Guidelines for thermographic inspection of concrete bridge components in shaded conditions[J]. *Transportation Research Record,* 2360 (1), 13-20 (**2013**), doi:10.3141/2360-02.

[32] de Freitas S. S., de Freitas, et al. (**2014**) Detection of façade plaster detachments using infrared thermography—A nondestructive technique[J]. *Construction and Building Materials* , Volume 70, Pages 80-87, doi: 10.1016/j. conbuildmat.**2014**.07.094.

[33] Scott M.; Kruger D. (2014) Infrared Thermography as a Diagnostic Tool for Subsurface Assessments of Concrete Structures[J]. *In Construction Materials and Structures* , IOS Press: Amsterdam, The Netherlands, pp. 904-909.

[34] Rumbayan R.; Washer G. A. Modeling of environmental effects on thermal detection of subsurface damage in concrete [J]. *Research in Nondestructive Evaluation* , 25, 235-252. doi: 10.1080/09349847.**2014**.933993

[35] Bauer E, de Freitas VP, et al. (**2015**), Infrared thermography - evaluation of the results reproducibility.[J] *Structural Survey* , Vol. 33 No. 1 pp. 20-35,doi: 10.1108/SS-05-2014-0021.

[36] Cotič P., Kolarič D., et al. (**2015**) Determination of the applicability and limits of void and delamination detection in concrete structures using infrared thermography[J], *NDT & E International* , Volume 74, Pages 87-93, doi:10.1016/j.ndteint. **2015**.05.003.

[37] Alfredo-Cruz R., Quintero-Ortiz L. A., et al. (**2015**) Non-destructive techniques in concrete elements for bridges' evalutation. *Revista Facultad de Ingeniería.* 24. 81-94.

[38] Khan F., Bolhassani M., et al. (**2015**) Modeling and experimental implementation of infrared thermography on concrete masonry structures[J]. *Infrared Physics & Technology* , Volume 69, Pages 228-237, doi: 10.1016/j. infrared.**2015**.02.001.

[39] Edis E., Flores-Colen, I. et al. Time-dependent passive building thermography for detecting delamination of adhered ceramic cladding. [J] *Nondestruct Eval 34* , 24 , doi:10.1007/ s10921-015-0297-5.

[40] Lai, W. W. -L.; Lee K. -K.; et al. (**2015**) Validation of size estimation of debonds in external wall's composite finishes via passive infrared thermography and a gradient algorithm [J]. *Construction and Building Materials* , Volume 87, Pages 113-124, doi:10.1016/j.conbuildmat.**2015**.03.032

[41] Watase A., Birgul R., et al (**2015**) Practical identification of favorable time windows for infrared thermography for concrete bridge evaluation[J]. *Construction and Building Materials, Volume* 101, Part 1, Pages 1016-1030, doi: 10.1016/j.conbuildmat.**2015**.10.156.

[42] Vaghefi K.; Ahlborn T. et al. (**2015**), C.N. Combined imaging technologies for concrete bridge deck condition assessment [J]. *Journal of Performance of Constructed Facilities* , 04014102, doi: 10.1061/(ASCE)CF.1943-5509.0000465.

[43] Bauer E. Pavon E., et al. (**2016**). Analysis of building facade defects using infrared thermography: laboratory studies[J]. *Journal of Building Engineering* , Volume 6, Pages 93-104, doi:10.1016/j.jobe.**2016**.02.012.

[44] Ellenberg A., Kontsos A, et al. (**2016**). Bridge deck delamination identification from unmanned aerial vehicle infrared imagery[J]. *Automation in Construction, Volume* 72, Part 2, Pages 155-165, doi:10.1016/j.autcon.**2016**.08.024.

[45] Huh J., Tran Q. H., et al. (**2016**) Experimental study on detection of deterioration in concrete using infrared thermography technique[J]. *Advances in Materials Science and Engineering.* 1053856, doi: 10.1155/**2016**.1053856.

[46] Hiasa S.; Birgul R. et al. (**2016**). Infrared thermography for civil structural assessment: demonstrations with laboratory and field studies[J]. *J Civil Struct Health Monit* 6, 619-636,

doi: 10.1007/s13349-016-0180-9

[47] Bauer E., Pavón E, et, al(**2016**). Criteria for identification of ceramic detachments in building facades with infrared thermography[J]. *In Recent Developments in Building Diagnosis Techniques; Delgado* , J. M. P. Q., Ed.; Springer: Singapore, pp. 51-68, doi: 10.1007/978-981-10-0466-7_4.

[48] Farrag S., Yehia S., et al. (**2016**). Investigation of mix-variation effect on defect-detection ability using infrared thermography as a nondestructive evaluation technique[J]. *Bridge Eng.* , 21, 4015055, doi: 10.1061/(ASCE)BE. 1943-5592.0000779.

[49] Sultan A., Washer G. (**2017**) A pixel-by-pixel reliability analysis of infrared thermography (IRT) for the detection of subsurface delamination[J]. *NDT & E International* , Volume 92, Pages 177-186, doi:10.1016/j.ndteint.**2017**.08.009

[50] Chiang L., Guo S. et al. (**2017**) The research of infrared thermal image diagnostic model for building external wall tiles[J]. *Advances in Technology Innovation. **2017*** , 2, 56-60.

[51] Hiasa S., Birgul R. et al. (**2017**) Investigation of effective utilization of infrared thermography (IRT) through advanced finite element modeling. *Construction and Building Materials* , Volume 150, Pages 295-309, doi: 10.1016/j. conbuildmat.**2017**.05.175.

[52] Hiasa S., Necati Catbas F, (**2017**) Considerations and issues in the utilization of infrared thermography for concrete bridge inspection at normal driving speeds[J]. *Journal of Bridge Engineering* , Volume 22, doi: 10.1061/(ASCE)BE. 1943-5592.0001124

[53] Janků M., Březina I. et al. (**2017**) Use of infrared thermography to detect defects on concrete bridges[J]. *Procedia Engineering* , 190, 62-69.

[54] Milovanovic B.; Banjad Pe ˇ cur, et al. (**2017**) The methodology for defect quantification in concrete using IR thermography. [J]. *Journal of Civil Engineering and Management* , 23, 573-582.

[55] Hiasa S.; Birgul R.; et al. (**2018**) Experimental and numerical studies for suitable infrared thermography implementation on concrete bridge decks[J]. *Measurement 121* , 144-159.

[56] Lourenço T., Matias L., et al. (**2017**) Anomalies detection in adhesive wall tiling systems by infrared thermography[J]. *Construction and Building Materials* , Volume 148, Pages 419-428, doi:10.1016/j.conbuildmat.2017.05.052.

[57] Hiasa S., Birgul R., et al. (**2017**). Effect of defect size on subsurface defect detectability and defect depth estimation for concrete[J]. *Nondestruct Eval* 36, 57, doi: 10.1007/s10921-017-0435-3.

[58] Escobar-Wolf R., Oommen T., et al. (**2018**) Unmanned aerial vehicle (UAV) -based assessment of concrete bridge deck delamination using thermal and visible camera sensors: a preliminary analysis[J]. *Research in Nondestructive Evaluation* , 29, 183-198.

[59] Güray E.; Birgül R. (**2018**) Determination of favorable time window for infrared inspection by numerical simulation of heat propagation in concrete[J]. *In Proceedings of the 3rd International Sustainable Buildings Symposium* , Dubai, United Arab Emirates, 15-17; pp. 577-591.

[60] Tran Q.; Huh J., et al. (**2018**) Effects of rebars on the detectability of subsurface defects in concrete bridges using square pulse thermography[J]. *NDT and E International.* 100, 92-100.

[61] Huh J.; Mac V.; et al. (**2018**) Detectability of delamination in concrete structure using active infrared thermography in terms of signal-to-noise ratio. [J]. *Applied Sciences* , 8, 1986

[62] Moropoulou A.; Avdelidis N.; et al. (**2018**) Multispectral applications of infrared thermography in the diagnosis and protection of built cultural heritage [J]. *Applied Sciences* , 8, 284.

[63] Rocha J. H. A.; Povoas Y. V.; et al. (**2018**) Detection of delamination in sunlight-unexposed concrete elements of bridges using infrared thermography. [J]. *Nondestructive Testing and Evaluation 38* , 8.

[64] Al Gharawi M.; Adu-Gyamfi Y.; et al. (**2019**) A framework for automated time-lapse thermography data processing. [J] *Construction and Building Materials* , 227, 116507.

[65] Cheng C.; Na R.; et al. (**2019**) Thermographic laplacian-pyramid filtering to enhance delamination detection in concrete structure[J]. *Infrared Physics & Technology* , 97, 162-176.

[66] Cheng C.; Shen Z. (**2020**) The Application of Gray-Scale Level-Set Method in Segmentation of Concrete Deck Delamination Using Infrared Images[J]. *Construction and Building Materials* . 240, 117974.

[67] Vyas V.; Patil, V. et al. (**2019**). Application of infrared thermography for debonding detection in asphalt pavements. [J]. *Civ Struct Health Monit* . 325-337, doi: 10.1007/s13349-019-00337-8.

[68] Cheng C., Shang Z., et al. (**2019**) Bridge deck delamination segmentation based on aerial thermography through regularized grayscale morphological reconstruction and gradient statistics,[J] *Infrared Physics & Technology* , Volume 98, Pages 240-249, doi:10.1016/j.infrared.**2019**.03.018.

[69] Milovanovic B., Gasi M.; et al. (**2020**) Principal component thermography for defect detection in concrete[J]. *Sensors* **2020**, 20(14), 3891.

[70] Pozzer S.; Pravia Z., et al. (**2020**) Statistical Analysis of Favorable Conditions for Thermographic Inspection of Concrete Slabs. [J] *Journal of Civil Structural Health Monitoring* . 10, 609-626.

[71] Raja B. N. K., Miramini, S., et al. (**2020**) The influence of ambient environmental conditions in detecting bridge concrete deck delamination using infrared thermography (IRT) [J]. *structural Control and Health Monitoring* . 27, e2506.

[72] Mirzabeigi S., Razkenari M. (**2022**). Automated vision-based building inspection using drone thermography. *Construction Research Congress **2022*** , 737-746.

[73] Mac V. H., Huh J., et al. (**2021**) A comprehensive study on identification of both deck and soffit defects in concrete bridge decks through thermographic investigation of shaded side under natural conditions. *Construction and Building Materials* , 303, 124452

[74] Zheng D., Tan S., et al. (**2021**) Research on the infrared thermographic detection of concrete under solar heating[J]. *Advances in Civil Engineering* , 6692729.

[75] Pozzer S.; Dalla Rosa F.; et al. (**2021**) Long-Term Numerical Analysis of Subsurface Delamination Detection in Concrete Slabs Via Infrared Thermography[J]. *Applied Sciences* , 11 (10), 4323, doi:10.3390/app11104323

[76] Puliti M., Montaggioli G., et al. (**2021**), Automated subsurface defects' detection using point cloud reconstruction from infrared images [J]. *Automation in Construction . Volume 129* , 103829, doi: 10.1016/j.autcon.**2021**.103829

[77] Angelosanti M., Kulkarni N., et al. (**2022**), Combination of building information modeling and infrared point cloud for nondestructive evaluation. *2022 IEEE International Workshop on Metrology for Living Environment , Cosenza, Italy* , **2022**, pp. 269-273.

[78] Pedram M., S. Taylor, et al. (**2022**). Experimental evaluation of heat transition mechanism in concrete with subsurface defects using infrared thermography. *Construction and Building Materials, Volume* 360, 129531, doi: 10.1016/j.conbuildmat.**2022**.129531.

[79] Williams J., Corvaro F., et al. (**2022**). Application of non-invasive active infrared thermography for delamination detection in fresco[J]. *International Journal of Thermal Sciences, Volume* 171, 107185, doi: 10.1016/j.ijthermalsci.**2021**.107185.

[80] Rakha, Tarek et al. (**2021**). 3D Drone-based time-lapse thermography: a case study of roof vulnerability characterization using photogrammetry and performance simulation implications. *Building Simulation 2021 Conference.* 30828. *IBPSA*

[81] Pan C. B., Wang J. Y., et al. (**2022**). Capsule network-based semantic segmentation model for thermal anomaly identification on building envelopes [J]. *Advanced Engineering Informatics, Volume* 54, 101767, doi: 10.1016/j.aei.**2022**.101767

[82] Ta Q., Mac V., et al. (**2023**). Nondestructive detection of delamination in painted concrete structures through square pulse thermography. *Journal of Building Engineering, Volume* 70, 106360, doi: 10.1016/j.jobe.**2023**.106360.

[83] Gil-Docampo M., Sanz J. O., et al. (**2023**). UAS IR-Thermograms Processing and Photogrammetry of Thermal Images for the Inspection of Building Envelopes[J]. *Applied Sciences* , 13(6):3948, doi: 10.3390/app13063948.

[84] Huh J., Mac, Van H., et al. (**2024**). Detection of sub-surface delamination and moisture penetration in unlined rock tunnels using passive thermography and tapping. *Jordan University of Science and Technology*; Volume: 18; *Issue* : 1

[85] Valluzzi M., Cardani G., et al. (**2025**). Optimization of infrared thermography investigations for identification of subsurface anomalies in plastered masonry walls[J]. *Construction and Building Materials, Volume* 494, 143329, doi: 10.1016/j.conbuildmat.**2025**.143329.

[86] Pozzer S., Ramos G., et al. (**2025**), Integration of thermographic inspection data with BIM for enhanced concrete infrastructure assessment[J], *Automation in Construction* , Volume 171, doi: 10.1016/j.autcon.**2025**.105965.

[87] Chen J., Zhang S., et al. (**2025**), Infrared thermography of façade delamination: Quantifying environmental variability and heat transfer mechanisms [J]. *Construction and Building Materials*, Volume 494, 143177, doi: 10.1016/j.conbuildmat.**2025**.143177.

[88] Zhang P., Teramoto A., et al. (**2025**). Application of various sensing techniques for post-earthquake damage assessment of exterior wall tiles, *Engineering Structures*, Volume 343, *Part A* , 120990, 10.1016/j.engstruct.**2025**.120990.

[89] International Organization for Standardization. (**2017**). Non-destructive testing—Infrared thermographic testing — General principles (ISO 10880:**2017**). ISO[S].

[90] Japan Institute of Building Technology. (**2019**). Guidelines for inspection of ceramic tile exteriors [In Japanese]. *Japan Institute of Building Technology Press, Tokyo, Japan* , pp. 12-38.

[91] Wang H. et al., (**2024**) A physical-constrained decomposition method of infrared thermography: pseudo restored heat flux approach based on ensemble bayesian variance tensor fraction [J], *IEEE Transactions on Industrial Informatics* , vol. 20, no. 3, pp. 3413-3424, doi: 10.1109/TII.2023.3293863

[92] Garrido L., Fernández E., et al. (**2023**). Automatic thresholding for infrared image segmentation in building defect detection. *Infrared Physics & Technology* , 132: 104658.

[93] Park S., Lee J., et al. (**2024**). CNN-based ROI segmentation for adaptive thresholding in building facade inspection. *Automation in Construction* , 168: 106892.

[94] International Organization for Standardization. (**2017**). Thermal bridges in building construction — Heat flows and surface temperatures — Detailed calculations (ISO 10211: **2017**).ISO.

[95] Sun Q.Y., et al. (**2007**). Acoustic inspection of wall hollowing based on SPCE61A single-chip microcomputer [In Chinese] [J]. *Technical Acoustics* , 6: 1150-1154, doi: CNKI: CDMD: 2.2008.058188.

[96] Wang H., Li J., et al. (**2024**). Experimental study on soil layer thickness investigation using ground-penetrating radar [In Chinese]. *Journal of Engineering Geology* , 32(2): 315-322.

[97] Ibarra-Castanedo C., Sfarra S., et al., (**2017**). Solar loading thermography: Time-lapsed thermographic survey and advanced thermographic signal processing for the inspection of civil engineering and cultural heritage structures[J]. *Infrared Physics & Technology* , Volume 82, Pages 56-74, doi: 10.1016/j.infrared.2017.02.014.

[98] Lai W., Chui L. and Sham, J. (**2024**) "Diagnosing External Wall Debond via Infrared Thermography: the Old and New approche," Hongkong Concrete institute, 05 01. [Online]

[99] Hong Kong Government Buildings Department, n. d. Mandatory Building Inspection Scheme [In English]. *[Online]* ; URL not provided.

[100] Chew M. Y. L., (**2021**). Façade inspection for falling objects from tall buildings in singapore[J]. *International Journal of Building Pathology and Adaptation* , Volume 41, Issue 6, Pages 162-183, doi:10.1108/IJBPA-10-2020-0087.

[101] Standardization Administration of China. (**2024**). GB/T 45166-2024 Non-destructive testing — Infrared thermographic testing — General principles [S]. China Standards Press.

[102] ASTM International. (**2022**). ASTM D4788-03(2022):

Standard Test Method for Detecting Delaminations in Bridge Decks Using Infrared Thermography[S]. https://www.astm.org/

[103] International Organization for Standardization (**2023**). *Performance of buildings — Detection of heat, air and moisture irregularities in buildings by infrared methods* [S]. Part 1: General procedures: ISO 6781-1:2023.

[104] Ministry of Housing and Urban-Rural Development of the People's Republic of China. (**2012**). *Technical specification for inspecting the defects of exterior walls cement coating of building with infrared thermography method* (JGJ/T 277-2012). China Architecture & Building Press.

[105] Singapore Government. (**2021**). Building Control (Periodic Inspection of Buildings and Building Façades) Regulations 2021. *Singapore Statutes Online* .

[106] ISO 9712: 2021, 2021). Non-destructive testing — Qualification and certification of NDT personnel. International Organization for Standardization (ISO), Geneva, Switzerland.

[107] Tonghuashun Finance, (**2024**). "Shenzhen Ruijie: AI + UAV empowers building inspection, defect detection rate increased to 93% [In Chinese]." [Online].

[108] Shenzhen Ruijie Engineering Consulting Co., Ltd., (**2023**). "A multi-modal intelligent recognition system for building external wall defects [In Chinese]."

[109] China Academy of Building Research, (**2023**). White Paper on Digital Technology for Building Operation and Maintenance [In Chinese]. *China Academy of Building Research* , Beijing, China, pp. 89-95.

[110] Guangxi Institute of Building Research & Design, (**2023**). "An adaptive enhancement system for building external wall images [In Chinese]." *Patent ZL202210567890.3*.

[111] Li Z., Liu Y., et al. (**2024**). 3D visualization of building facade defects by fusing AI detection and BIM. *Automation in Construction* , 160: 106520.

[112] Shiwei Intelligent Technology (Shanghai) Co., Ltd., (**2023**). "An automatic four-dimensional space flight system [In Chinese]." *Patent ZL202310123456.7* .

[113] Wei J., Shi Q., et al. (2025) Multi-component controllable diversified augmentation of industrial images based on feature disentanglement, Engineering Applications of Artificial Intelligence, vol. 160, p. 111963, 10.1016/j. engappai.**2025**.111963.

[114] Sun H., Cao Y., et al. (**2024**) Unseen visual anomaly generation[J], *arXiv preprint arXiv:2406.01078*, doi:10.48550/ arXiv.2406.01078.

[115] Yu Z., Liu C., et al, (**2025**) MetaEarth: A generative foundation model for global-scale remote sensing image generation[J], *IEEE Transactions on Pattern Analysis and Machine Intelligence* , vol. 47, no. 3, pp. 1764-1781. doi: 10.1109/TPAMI.**2024**.3507010.

[116] Wang J., Wang K., et al. (**2025**), Self-improving generative foundation model for synthetic medical image generation and clinical applications[J], *Nature Medicine* , vol. 31, pp. 609-617. doi: 10.1038/s41591-024-03359-y.

[117] Meng C., Zhu W., et al. (**2024**) Multi-distortion suppression for neutron radiographic images based on generative adversarial network[J], *Nuclear Science and Techniques* , vol. 35, p. 81. doi: 10.1007/s41365-024-01445-x.

[118] Park T., Efros A., et al. (**2020**) Contrastive learning for conditional image synthesis, *Proceedings of the European Conference on Computer Vision* (ECCV).

[119] Wang H., Li N., et al. (**2024**) Mappingformer: learning cross-modal feature mapping for visible-to-infrared image translation[J]. *Proceedings of the 32nd ACM International Conference on Multimedia* (*MM '24*), pp. 10745-10754. doi: 10.1145/3664647.3681375.

[120] Li N., Wang H., et al. (**2025**), Cross-Modal visible-to-infrared image translation in remote sensing guided by thermal features[J]. *IEEE Transactions on Geoscience and Remote Sensing, vol*. 63, pp. 1-16, Art. no. 5628916. doi: 10.1109/ TGRS.2025.3579267.

[121] Schulz E., Speekenbrink M., et al. (**2018**) A tutorial on Gaussian process regression: Modelling, exploring, and exploiting functions[J]. *Journal of Mathematical Psychology* , Volume 85, Pages 1-16, doi: 10.1016/j.jmp.2018.03.001.

[122] Segal M R.(**2004**) Machine learning benchmarks and random forest regression. *Center for Bioinformatics and Molecular Biostatistics* , 4(14): 1-14.

[123] Yao W, Chen X, et al. (**2011**). Concurrent subspace width optimization method for RBF neural network modeling. *IEEE transactions on neural networks and learning systems* , 23(2): 247-259.

[124] Zhao T., Zhou Y., et al. (**2021**). Solving the direct and inverse problems of heat conduction equation based on embedded physical mechanism neural network [J]. *Journal of Aerodynamics* ,39(05):19-26.

[125] Li Z., Qin J., et al. (**2021**). Construction of physical field surrogate model of heat transfer process based on physical information neural network[J]. *Journal of Chemical Industry* , 2021,72(03):1496-1503.

[126] Zobeiry N., Humfeld K. D. (**2021**). A physics-informed machine learning approach for solving heat transfer equation in advanced manufacturing and engineering applications. *Engineering Applications of Artificial Intelligence, volume* 101, doi:10.1016/j.engappai.2021.104232.

[127] Bo Y., Xu M., et al. (**2023**) Functional gradient material steady-state/transient heat conduction analysis based on physics-informed neural networks [J]. *Journal of Computational Mechanics* , 40(04):594-601.

[128] Shukla K, Jagtap A D, et al. (**2022**) A physics-informed neural network for quantifying the microstructural properties of polycrystalline nickel using ultrasound data: a promising approach for solving inverse problems[J]. *IEEE Signal Processing Magazine*, 39(1): 68-77, 10.1109/MSP.2021. 3118904.

[129] Yang H., Yan Y., et al. (**2024**) Evaluating efficiency of foreign object detection technology based on the use passive infrared thermography[J]. *Russ J Nondestruct Test* 60, 888-897. doi: 10.1134/S106183092460206X.