

Systematic Review

Infrared Thermography in Maritime Systems: A Systematic Review

Lucija Tadić, Ivana Golub Medvešek , Igor Vujović  and Joško Šoda * 

Faculty of Maritime Studies, University of Split, 21000 Split, Croatia; ltadic1@pfst.hr (L.T.); igolub@pfst.hr (I.G.M.); ivujovic@pfst.hr (I.V.)

* Correspondence: jsoda@pfst.hr

Abstract

The maritime industry is undergoing a digital transformation, in which predictive maintenance and intelligent diagnostics play a crucial role in enhancing operational safety and efficiency. This paper investigates the application of infrared thermography (IRT) for fault detection and condition monitoring of ship machinery, with particular emphasis on its integration within condition-based and predictive maintenance frameworks. A systematic review was conducted in accordance with the PRISMA 2020 methodology, analyzing 210 publications retrieved from the Web of Science (WoS), Scopus, and Google Scholar databases to identify prevailing technological trends and research gaps. The results indicate that IRT enables early detection of critical faults such as overheating, insulation degradation, and poor electrical connections, thereby reducing unplanned downtime and improving system reliability. When integrated with artificial intelligence (AI), deep learning (DL), and convolutional neural networks (CNNs), diagnostic accuracy can be automated through enhanced data interpretation. Despite its proven effectiveness, standardized protocols and real-world validation of IRT–AI systems remain limited in the maritime sector. IRT is therefore recognized as a key enabler of safer, smarter, and more sustainable ship maintenance within the broader maritime digitalization framework.

Keywords: infrared thermography (IRT); fault detection and diagnosis; maritime digitalization; predictive maintenance; intelligent automation; condition-based monitoring



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1. Introduction

The maritime industry is an important aspect of the global economy and logistics, enabling the transport of the vast majority of the world's traded goods. Its strategic importance demands the highest operational efficiency, safety, and environmental responsibility standards. Despite its economic significance, the maritime sector remains a major contributor to global emissions. According to the IMO Fourth GHG Study (2020), international shipping emitted approximately 1076 million tons of CO₂-equivalent in 2018, representing nearly 3% of global anthropogenic emissions [1–3]. To address this environmental footprint, the International Maritime Organization (IMO) has set ambitious decarbonization targets: a 40% reduction in carbon intensity by 2030 and a 70% reduction by 2050 relative to 2008 levels [4]. These targets underscore the need for advanced energy-efficiency solutions and intelligent maintenance strategies, including the use of infrared thermography for proactive condition monitoring. However, the maritime sector still lacks harmonized diagnostic and measurement protocols specific to infrared thermography. Existing ISO and IEC standards define general procedures for industrial thermography, but they do not fully account for

shipboard conditions such as fluctuating thermal loads, high humidity, salt contamination, metallic reflections, restricted access, and rapidly changing ventilation patterns. As a result, there is currently no standardized framework that ensures consistent emissivity estimation, measurement geometry, environmental compensation, or validation procedures onboard ships [5–9]. In such a complex and demanding environment, the reliability and safety of propulsion systems and equipment are not only operational priorities but also legal imperatives defined by strict international regulatory frameworks. Failures in ship systems can have catastrophic economic, social, and ecological consequences, ranging from endangering human lives and cargo loss to long-term damage to marine ecosystems. For this reason, international conventions such as the International Convention for the Safety of Life at Sea (SOLAS) and the International Convention for the Prevention of Pollution from Ships (MARPOL) impose strict requirements for maintenance and monitoring. In addition to physical failures, recent research emphasizes the growing importance of assessing the vulnerability of shipboard systems to cyber and operational technology risks, as these factors also affect the overall reliability and safety of maritime operations [10]. One key aspect is fire prevention, as hot surfaces in engine rooms are the most common ignition sources. The SOLAS convention stipulates that the maximum surface temperature of machinery must not exceed 220 °C [11].

The traditional reactive maintenance model, which relies on repairs after failures, is increasingly being replaced by proactive strategies. It is believed that the future of maintenance practices lies in condition-based approaches. Condition-based maintenance (CBM) and predictive maintenance (PrM) are becoming the standard as they enable early detection of anomalies and planning of servicing before downtime occurs. The application of CBM can extend overhaul intervals by up to 50% and reduce maintenance costs by 25–45%. Despite these advantages, only 10% of the maritime industry currently applies the CBM approach, highlighting a significant gap between potential and practice [12]. Recent studies provide frameworks and systems for implementing CBM and PrM in industrial and transport systems, including sensor selection, thermal data processing, and model evaluation, with an emphasis on integration with machine learning (ML) and AI methods [13–17]. Approaches for automated thermal data processing have been specifically addressed, including the transition from laboratory systems to field conditions in ship systems and the application of interpretable models under variable load [18–20]. These papers also show a trend of increasing the reliability and speed of diagnostics through the combination of IRT technology, sensor networks, and real-time data processing [13,18,19].

In the search for tools to support proactive maintenance, infrared thermography (IRT) stands out as an extremely effective, non-destructive technique, ideally suited to the complex, often inaccessible environment of a ship's engine room. Unlike traditional methods such as vibration analysis, which require contact measurements and are sensitive to noise, IRT offers unique advantages: it is a non-contact, fast, reliable, and precise technique that allows scanning of large areas in a very short time without system shutdown [20]. Recent studies demonstrate the application of automated thermal image processing, the integration of radiometric measurements, and methods for emissivity correction, which allow integration with CBM and PrM systems [13–15]. Furthermore, recent papers demonstrate integrated systems that combine IRT and edge computing to enable rapid anomaly detection in industrial components, particularly within the maritime and energy sectors [13,15–19].

As a contactless method, IRT enables fast and safe surface temperature measurement, visualizing thermal patterns that indicate potential mechanical or electrical problems such as friction, poor connections, insulation issues, or irregularities in cooling systems. Its potential has been recognized as crucial for maintenance optimization. In the near future, ship machinery will also benefit from thermal imaging of system conditions, particularly as a

strategy for identifying equipment and systems in need of maintenance and eliminating unnecessary work [21]. IRT is a useful tool in the maritime industry, enabling non-destructive, fast, and reliable real-time system diagnostics. Its applications cover a wide range of areas. In electrical systems, it allows for early detection of overheating in conductors, switches, and motors, thereby preventing failures and fires, and enabling maintenance based on actual condition. For mechanical components, IRT is essential for detecting bearing failures, which account for over 40% of failures in large electric motors, and can identify problems such as misalignment and operational overload [22]. In propulsion systems, it is used to monitor diesel engines, turbochargers, and cooling systems, while in tanks and pipelines, it is used to check thermal insulation and detect leaks, which is especially important for LNG/LPG vessels. Thermography is also useful in monitoring solar and electronic systems, particularly on modern ships with hybrid propulsion. Besides its technical benefits, IRT contributes to ship safety by detecting potentially hazardous hot spots early and serves as documented evidence of technical condition for inspections and classification societies. The implementation of IRT results in greater reliability, safety, and cost-effectiveness of ship systems [11,13,23].

The integration of thermography with artificial intelligence (AI) and advanced data architectures represents the future of predictive maintenance in the maritime sector. These systems enable automation, increase objectivity and diagnostic accuracy, and address key challenges related to data scarcity and real-time processing. Automated diagnostics using AI and convolutional neural networks (CNN) is a key step forward. CNNs are deep learning models that automatically analyze thermograms and classify faults without human expertise. Comparative results show that IRT-based methods offer a promising tool for diagnosing faults in rotating machinery, outperforming vibration-based methods, which in some tests achieved only 75.38% accuracy. When using only thermographic images, the model achieved 100% classification accuracy in all tested conditions [23,24]. Recent research also shows that generative models (GANs), transfer learning, and edge-cloud architectures can increase reliability and reduce communication overhead in maritime applications [8–19].

The main issue is that, despite proven technology, IRT is still rarely used in maritime systems, and scientific research has specific limitations. A large portion of papers focuses on rotating machines under stable, laboratory conditions, while there is a lack of research on early fault diagnosis of reciprocating machinery, such as diesel engines, using IRT [25]. Additionally, there is limited research on diagnosing rotating machinery under variable-speed conditions using IRT, which is a common scenario in ship propulsion systems [26]. Moreover, recent reviews emphasize the need to evaluate IRT-AI systems under actual ship-board conditions, proposing validation protocols and measurement standardization [8–19]. Nevertheless, its application in the maritime sector is becoming increasingly recognized. To foster greater adoption of this diagnostic method for ship maintenance, it is crucial to encourage shipowners to support crews in adopting new onboard technologies that enhance navigational safety. However, it should be noted that calibration and metrological support aspects in the context of NDT are not included in this work, as the focus is on reviewing the applications of IRT in diagnostics and condition monitoring.

The purpose of this paper is to provide a comprehensive analysis of research and technologies related to the application of infrared thermography (IRT) in fault diagnosis and condition monitoring of maritime systems. By evaluating current progress and trends in this field, the paper assesses the technological maturity of IRT-based methods and emphasizes the need for regulatory and operational adaptation to support their adoption in the maritime domain. The study is based on a systematic literature review conducted using the PRISMA 2020 methodology, which ensured a transparent and high-quality selection

of scientific sources through well-defined search criteria, keywords, and logical operators for each database. By synthesizing the available findings, the paper aims to demonstrate that IRT represents an effective, cost-efficient, and reliable diagnostic technique. When properly integrated into maintenance strategies, IRT enhances navigational safety, reduces the likelihood of catastrophic failures, optimizes maintenance costs, and improves the environmental sustainability of maritime operations. This paper aims to systematically investigate, classify, and analyze scientific research on the application of infrared thermography in maritime systems using the PRISMA 2020 methodology. The specific objectives are as follows:

1. Identify technological trends and research gaps related to IRT-based condition monitoring and fault diagnosis in ship machinery.
2. Evaluate the integration of IRT with AI, DL, and IoT technologies.
3. Propose directions for future research and standardization of IRT-driven predictive maintenance strategies in the maritime sector.

This paper hypothesizes that the application of infrared thermography (IRT) as a proactive diagnostic tool for fault detection and maintenance in maritime systems significantly reduces unplanned downtime and overall maintenance costs compared to traditional reactive approaches.

Finally, the structure of the proposed article is as follows: After the introduction, Section 2 outlines the approach to the systematic literature review. Section 3 presents the results and discussion derived from the methodology. Section 4 provides conclusions and recommendations for future work and the development of IRT in the maritime sector.

2. Review Methodology

This paper applies a systematic literature review approach based on the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which is widely recognized as a global standard for ensuring transparency, reproducibility, and methodological rigor in research synthesis. The review protocol was registered in the Open Science Framework (OSF) and includes the study objectives, inclusion and exclusion criteria, as well as the core methodological framework. A more detailed version of the protocol, including the complete Generalized Systematic Review template, is available within the OSF Project and in the Supplementary Materials Section. This approach ensures transparency and reproducibility in accordance with PRISMA 2020 guidelines. The PRISMA approach, initially designed for systematic and transparent research synthesis, has since been successfully adapted to various engineering and applied sciences.

2.1. Search Strategy and Selection Process

The PRISMA application in the maritime context has been confirmed in numerous systematic reviews on specific topics, such as port-related gas emissions and communication technologies for signaling facilities [27–29]. When combined with bibliometric methods, it allows for the detection of research trends, publication frequency, and thematic clusters, as demonstrated in reviews of big data, AI, and digital transformation in the shipping industry [30,31]. This approach ensures that the review not only summarizes existing studies and highlights underexplored areas relevant to infrared thermography (IRT) applications in the maritime industry.

An overview of the research workflow, including the definition of the aims, objectives, and hypothesis; structured database searches; screening and eligibility assessment; and the final thematic synthesis, is presented in Figure 1.

Figure 1 outlines the step-by-step methodological workflow adopted in this systematic review. The process begins with defining the research aims, objectives, and hypothesis,

followed by keyword identification and systematic literature searches in the Web of Science, Scopus, and Google Scholar databases. The subsequent stages involve screening and applying inclusion and exclusion criteria, conducting a full-text assessment, and classifying the selected studies thematically. Finally, the reviewed papers were analyzed to identify methodological patterns, technological developments, and research gaps related to infrared thermography for maritime applications.

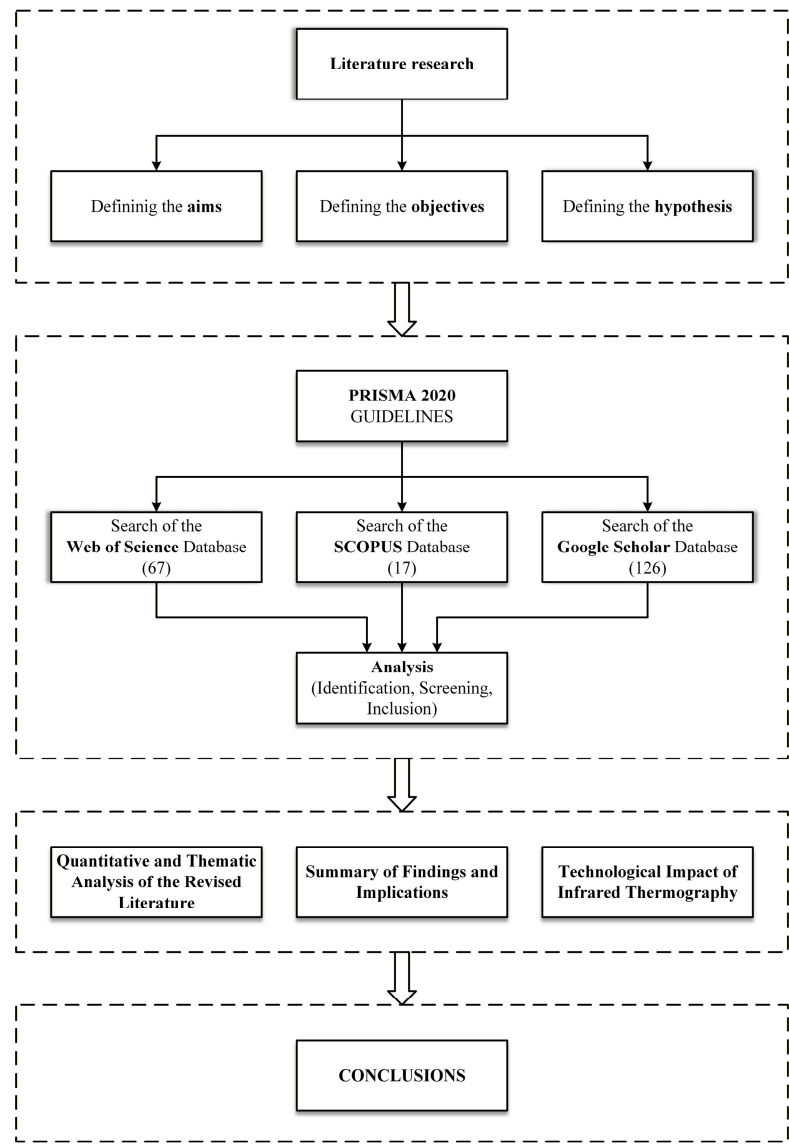


Figure 1. Methodological framework of the proposed research.

The literature search strategy was designed to identify studies relevant to infrared thermography applications in the maritime industry. Specific keywords and Boolean operators were defined for each database to ensure precise and comprehensive retrieval of publications. Table 1 summarizes the search parameters applied to Web of Science, Scopus, and Google Scholar.

The selected search strategy ensured that the most relevant and up-to-date research papers were included, covering the period 2015–2024, in line with the objectives of this thesis. These databases provide comprehensive coverage of peer-reviewed journal articles and conference papers on the application of thermography and AI in maritime systems.

Table 1. Database-specific search strings.

Database	Keywords and Boolean Operators
Web of Science	("infrared thermography") AND ("fault diagnosis" OR "condition monitoring") AND ("maritime industry" OR "marine systems")
Scopus	TITLE-ABS-KEY ("infrared thermography" OR "thermal imaging") AND ("machine learning") AND ("predictive maintenance" OR "electrical systems") AND ("maritime" OR "ship" OR "vessel" OR "marine") AND PUBYEAR > 2014 AND PUBYEAR < 2025
Google Scholar	("thermography" OR "infrared thermography") AND ("vessel" OR "ship monitoring" OR "real-time monitoring" OR "IRT sensors") AND ("anomaly detection" OR "fault diagnosis") AND (marine engineering" OR "maritime industry" OR "marine" OR ships") AND ("condition monitoring" OR "predictive maintenance") AND ("deep learning")

2.2. Synthesis Methods and Quality Appraisal

Due to the significant heterogeneity of the included papers, a quantitative meta-analysis was not performed. Consequently, the effect measures were not applicable. A narrative and thematic synthesis method was employed. Data were prepared, tabulated (as shown in Tables 2 and 3), and grouped by key themes, including technological trends, specific components, and AI/DL integration.

A formal risk-of-bias assessment for each study was not conducted using a standardized tool. Instead, the methodological quality and rigor of the studies were critically appraised during the data extraction phase, particularly for the 12 seminal papers. This qualitative appraisal informed the synthesis and the discussion of limitations. A formal assessment of reporting bias was not performed. The certainty in the body of evidence was evaluated qualitatively based on the consistency of findings across studies and the identified methodological rigor.

3. Results and Discussion

Building on the methodological framework outlined in Section 2, the results from the WoS, Scopus, and Google Scholar databases are presented below. The literature search utilized the keyword combinations listed in Table 1, covering the period from 2015 to 2024. A total of 210 relevant scientific papers were identified and systematically organized following the PRISMA 2020 guidelines, as shown in Figure 2.

Figure 2 shows the process of literature selection and analysis conducted in accordance with the PRISMA 2020 guidelines. The process comprises three main stages: document identification, screening, and inclusion in the final corpus.

In the identification stage, a systematic search was performed across three databases: Web of Science (67 papers), Scopus (17 papers), and Google Scholar (126 papers). A total of 210 potentially relevant papers were identified based on predefined keywords and Boolean operators. This stage established the foundation for subsequent evaluation and refinement. The screening stage was conducted in two steps. The first step involved removing duplicates resulting from database overlap. A total of 16 duplicates were eliminated, leaving 194 unique papers for further consideration. In the second step, titles and abstracts were reviewed according to the following exclusion criteria:

- The topic was not related to infrared thermography (IRT) fault diagnosis.
- The paper was not written in English.
- The document was an integral part of a published book.
- The study was not fully applicable to technical systems in the maritime sector.

Based on these criteria, 154 papers were excluded, leaving 40 papers that met the inclusion requirements. During the inclusion stage, the remaining papers were fully analyzed to

verify their relevance and methodological quality. The Web of Science (WoS) database accounted for the largest share, with 20 papers (50%), followed by Google Scholar with 14 papers (35%) and Scopus with six papers (15%). This distribution highlights the dominant role of WoS in providing high-quality, relevant research publications, while Google Scholar and Scopus complement the dataset with additional, often interdisciplinary, sources.

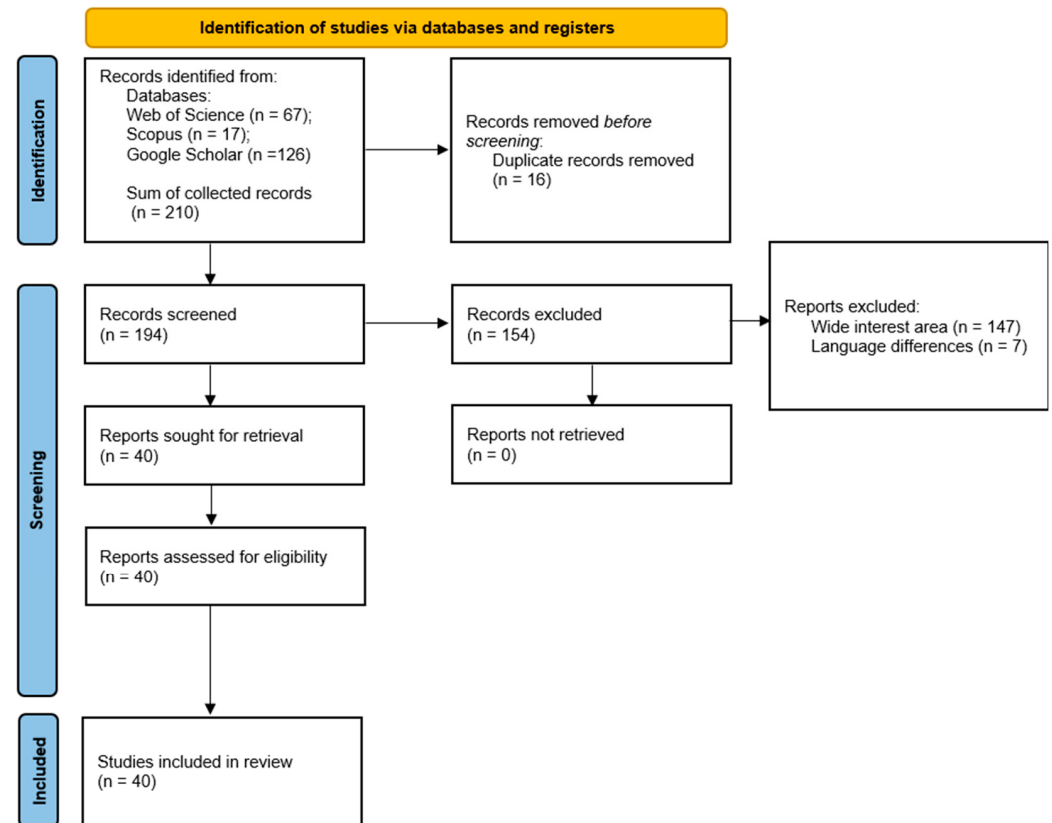


Figure 2. PRISMA flowchart of the literature identification, screening, and inclusion process.

Furthermore, a subsequent qualitative assessment identified 12 key papers distinguished by methodological rigor, innovation, and direct applicability of IRT technology within the maritime context. This in-depth selection was conducted to identify the most representative and influential studies, enabling a focused analysis of the current state of research, technological maturity, and remaining gaps that shape the practical adoption of IRT in maritime systems. This three-phase process ensures transparency, reproducibility, and scientific reliability, fully consistent with the PRISMA 2020 methodological framework [27].

3.1. Quantitative and Thematic Analyses of the Reviewed Literature

Building upon the systematically selected collection of 40 papers, this section provides a quantitative and thematic analysis of the reviewed literature. The aim is to identify publication dynamics, research trends, and the main technological directions related to the application of infrared thermography in fault diagnosis and condition monitoring within the maritime industry. The annual distribution of the 40 published scientific papers on infrared thermography in maritime applications in the period from 2015 to 2024 is presented in Figure 3.

To quantify the observed trend, a least-squares regression line was fitted to the data, minimizing the squared deviations between the actual number of publications and the fitted values. The resulting slope of 19.98° indicates a steady increase in publications over the examined decade, highlighting a growth trend. As shown in the figure, the highest number

of papers was published in 2023, while the lowest outputs occurred in 2015 and 2020. In 2024, six papers were published, compared to five papers in 2017, 2018, and 2021, and four in 2019, while 2022 saw three publications. Overall, the analysis demonstrates consistent growth in research on infrared thermography in the maritime industry, underscoring the technology's relevance and continued interest.

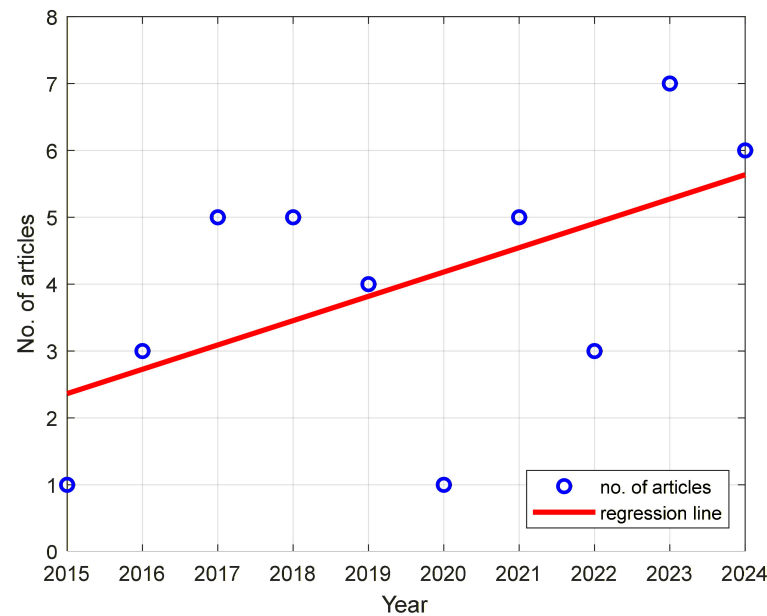


Figure 3. Annual distribution of the papers included in the systematic review (2015–2024).

In the context of the increasing complexity of systems in the maritime industry and the growing need for proactive maintenance, understanding the role of modern technologies in fault diagnostics has become imperative. This analysis provides an overview of key concepts and technologies discussed in the 40 selected scientific papers, with their interrelations illustrated in Figure 4.

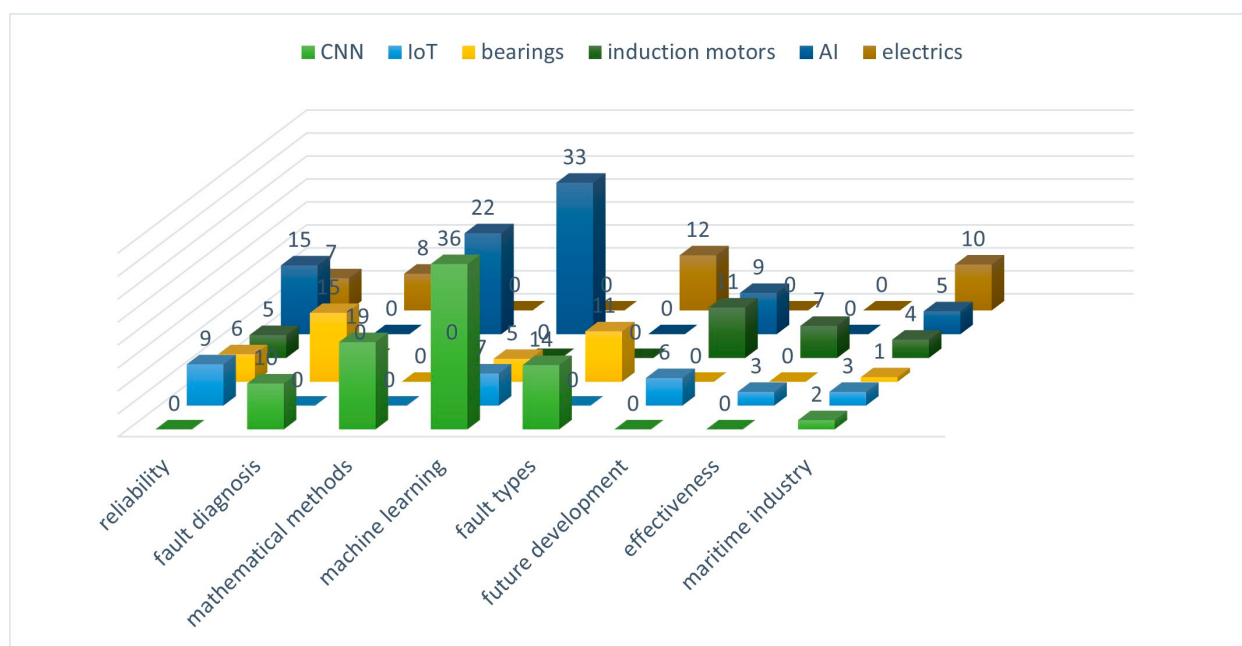


Figure 4. Distribution of key technologies and concepts across research areas related to fault diagnosis.

Figure 4 visualizes the multidimensional interconnections between technologies, research domains, and specific components within the analyzed corpus. The visualization adopts a cumulative approach, where individual studies are mapped to multiple intersecting categories (e.g., a single paper that uses a CNN for bearing fault diagnosis is represented in both respective clusters), reflecting the highly multidisciplinary nature of current research.

The chart reveals a dominant concentration at the intersection of machine learning and fault diagnosis, driven largely by CNN (green bars) and AI technologies. A critical analysis suggests that while deep learning architectures are well-established in broader industrial applications, their intensive integration into maritime IRT is a more recent trend, peaking specifically in the 2020–2024 period. Regarding physical assets, bearings and induction motors emerge as the primary subjects of investigation due to their susceptibility to thermal faults.

However, a significant disparity is visible in the lower frequencies for the ‘Maritime Industry’ and ‘Reliability’ categories compared to those in algorithmic domains. This highlights a clear research gap: while algorithmic accuracy has advanced significantly in simulated environments, studies validating these models under complex, real-world shipboard conditions and quantifying their impact on long-term system reliability remain less developed compared to pure fault classification efforts.

The analysis showed that the largest share of the relevant papers [20,22–25,32–46] is published by the IEEE (Institute of Electrical and Electronics Engineers), reflecting the strong technological and engineering orientation of infrared-thermography-based diagnostics. Contributions from the MDPI (Multidisciplinary Digital Publishing Institute) papers [13,47–52] follow, frequently covering sensor technologies, applied diagnostics, and intelligent maintenance. Finally, a substantial number of papers were also published by national publishers [11,12,21,26,53–58]. Elsevier ranks fourth [1,59,60], indicating additional diversity in publication sources and regional research efforts. This distribution underscores the primarily technical and application-driven nature of IRT research in fault detection and predictive maintenance with the maritime sector.

Building on this publisher-level distribution, a thematic analysis of the reviewed papers offers deeper insight into the field’s core research directions. That analysis revealed that IRT consistently appears as the central concept, forming the primary thematic cluster due to its established role in thermal diagnostics and condition monitoring. Closely associated secondary themes include fault diagnosis, maritime applications, and the integration of IRT within data-driven maintenance frameworks, reflecting the practical orientation of thermographic methods toward ensuring ship reliability and safety. A third group of topics represents tertiary, emerging technological domains, most notably artificial intelligence, convolutional neural networks, vibration analysis, edge computing, and hybrid sensor networks. These areas are increasingly incorporated into IRT-based diagnostic workflows, indicating a shift from conventional thermal inspection toward intelligent, automated, and computationally enhanced maintenance strategies. Together, these primary, secondary, and tertiary thematic categories illustrate the progressive digitalization of maritime engineering systems and the growing convergence between thermography, smart sensing, and artificial intelligence.

To enable a more robust quantitative interpretation of the literature, twelve papers were selected through detailed examination. This subset was selected using broad qualitative criteria, including methodological clarity, relevance to maritime systems, demonstration of IRT-based fault diagnosis, and alignment with the dominant thematic clusters identified in the full dataset. The selected papers, therefore, serve as representative examples rather than an exhaustive or ranked list.

Table 2 serves as a foundation for further discussion and comparative analysis in this chapter, particularly regarding the application of advanced data processing methods and fault diagnosis in the maritime context. It is important to emphasize that the common characteristics include the use of thermography, the application of deep learning, and a focus on system reliability under real operating conditions.

Table 2. Leading representative papers emerging from the analyzed literature.

Application Area	Representative Studies (Ref. No.)	Methodological Contribution	Key Insights
Fire Safety and Ship Engine Rooms	[11]	Low-cost hybrid thermography	Demonstrated viability of affordable IRT for detecting overheated surfaces (>220 °C) in ship engine rooms; highlighted insulation deficiencies and operational risks.
Industrial IRT—General Reviews	[20]	Review of industrial applications	Summarized major advances in IRT technologies, highlighting relevance for electrical and mechanical systems and identifying persistent limitations.
Marine Engines and Pistons	[21]	Experimental fault detection	Verified use of IRT for monitoring marine piston engines under different loads, confirming reliable detection of abnormal thermal patterns.
Rotating Machinery Fault Diagnosis (Traditional Approaches)	[22,24,37]	Thermographic fault analysis in induction and rotating machines	Showed that IRT can detect bearing, misalignment, and cooling faults even where vibration analysis fails; confirmed robustness under variable loads.
ML-Based Fault Detection (CNN & Deep Learning)	[23,25,55]	CNN, statistical thermography, hybrid DL	Achieved high diagnostic accuracy, including for multiple and compound bearing faults; demonstrated potential for predictive maintenance.
Advanced AI and Data Augmentation	[26,45]	cGAN, YOLOv8, edge–cloud computing	Improved detection accuracy and robustness via augmented datasets and real-time AI-assisted monitoring; suitable for autonomous operation.
Specialized Applications (Pumps & Cavitation)	[59]	Thermalindex, image processing	Confirmed IRT effectiveness in identifying cavitation and air entrainment in centrifugal pumps, enabling earlier detection than acoustic or vibration methods.

In the context of research on the application of IRT in maintenance and fault diagnosis, an analysis of scientific output was conducted across leading databases. The relative distribution of publications identified through keyword searches for equipment categories on which IRT-based testing and maintenance have been conducted is presented in Figure 5.

The distribution, presented in Figure 5, highlights the specific focus areas of individual databases within the field of maintenance. From the WoS indexed database, it can be observed that the majority of the remaining papers were published in the ‘Induction engines’ theme, an area which is crucial for industrial maintenance. Also, the ‘Rotating machinery’ and ‘Internal combustion engines’ are significantly represented in the WoS. Contrary, the Scopus database has a very strong coverage of the ‘Other equipment’ category (which likely includes bearings, couplings, and similar items), while the Google Scholar database only covers the ‘Internal combustion engines’ segment. This result suggests that to obtain the most comprehensive overview of research on IRT applied to industrial components, it is essential to consult both the WoS-indexed and Scopus databases.

Furthermore, various authors have noted that the development of IRT in fault diagnosis and maintenance is increasingly focused on integrating measurement techniques, computational analytics, and automated decision-making [61–64]. This trend positions IRT as a key element of modern condition-monitoring systems, particularly in industrial and maritime environments where detection speed and measurement reliability are critical [65–67].

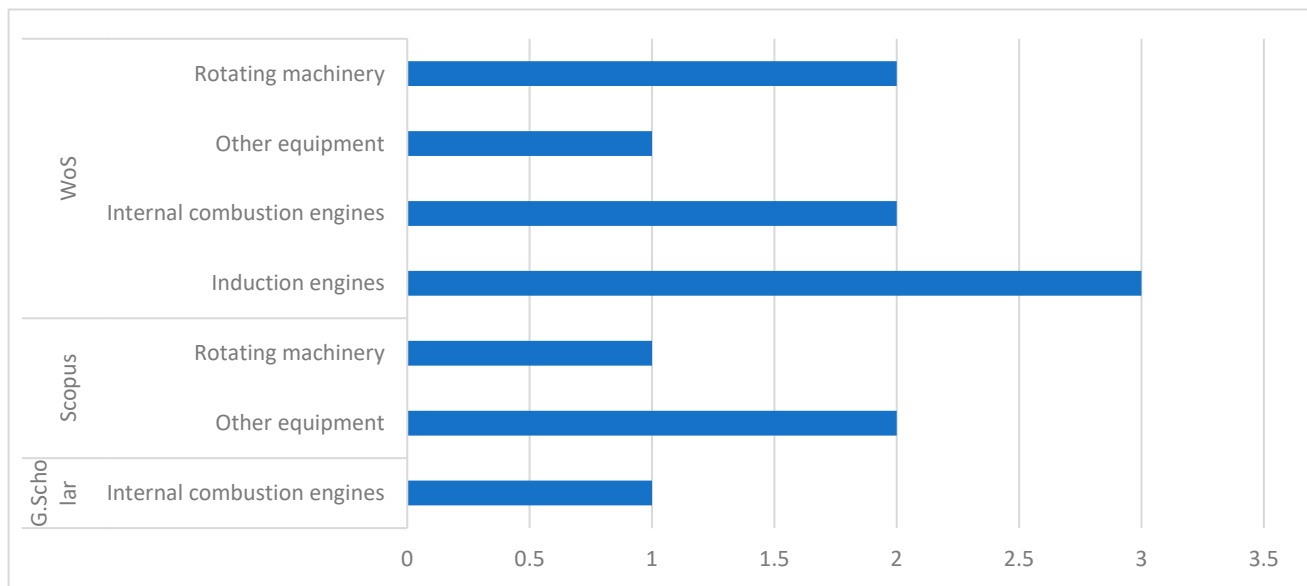


Figure 5. Thematic and technological categorization of the reviewed literature.

From a meteorological perspective, several studies emphasize the need for standardized procedures and sensor calibration to reduce measurement uncertainty, especially under dynamic operational conditions [68–70]. At the same time, however, the use of IRT in combination with smart sensors, edge computing, and deep learning methods has become more pronounced, enabling timely anomaly identification and optimization of predictive maintenance strategies [71–75].

Recent research also highlights the importance of an interdisciplinary framework that merges thermography, computer vision, and artificial intelligence into a unified diagnostic approach [76–80]. Such integration enhances the interpretation of thermal patterns, improves the accuracy of condition assessment, and supports more efficient real-time decision-making [81,82].

On this foundation, the following subsection presents a comparative analysis of the research focus and technical components identified across the reviewed databases and thematic clusters.

3.2. Comparative Analysis of Research Focus by Databases and Technical Components

A detailed methodological comparison was performed for the twelve key papers identified in this study. The analysis aimed to highlight the common research approaches, methodological limitations, and areas of process in the application of infrared thermography (IRT) in the maritime industry. Table 3 summarizes the methodological approaches extracted from all 40 reviewed papers, presented as grouped categories, rather than individual paper entries.

The papers presented in Table 3 indicate that most studies concentrate on rotating machinery, induction motors, and bearings, components that are both fundamental to ship propulsion systems and prone to thermally observable failure modes. The majority of experiments rely on FLIR (Forward-Looking Infrared) or similar infrared cameras, while only one study [11] employs a hybrid approach based on safety sensors. Most investigations were conducted under controlled laboratory conditions, with relatively few studies measuring in real shipboard environments, despite their significant value for realistic system assessment, as demonstrated in [20,22].

Furthermore, data processing techniques range from basic temperature analysis to advanced deep-learning approaches, including CNNs, GANs, and edge–cloud architec-

tures [32]. A notable trend is the increasing integration of machine learning models with thermographic data, enabling automation and improving the precision of fault classification. However, these advanced approaches are constrained by the limited availability of large, high-quality datasets in real maritime practice, highlighting a persistent gap between experimental research and operational shipboard implementation.

Table 3. Methodological patterns across the analyzed literature.

Thematic Cluster	Dominant Approaches Identified in the Literature	Key Findings Across Studies	Main Limitations Highlighted	Future Research Directions
Diagnostic of Electrical Systems	Threshold-based detection, statistical analysis, hotspot monitoring	Reliable identification of overheated contacts, insulation degradation, and connection faults; suitable for routine maintenance	Strong sensitivity to emissivity and reflections; limited performance in high-humidity or low-resolution settings	Development of emissivity-compensation workflows and maritime-specific inspection protocols
Rotating Machinery & Engines	CNN-based classification, transfer learning, thermogram segmentation	High accuracy in detecting bearing, rotor, and misalignment faults under controlled conditions; IRT effective even where vibration analysis fails	Reduced accuracy under variable loads, vibration, and engine room interference; data scarcity for maritime assets	Multimodal fusion (IRT + vibration), domain adaptation techniques, creation of maritime-specific datasets
Predictive Maintenance & Condition-Based Monitoring (CBM)	Hybrid ML, LSTM models, anomaly detection	Enables early identification of anomalous thermal behavior and supports predictive maintenance strategies	Limited validation on operational vessels; computational constraints for shipboard deployment	Edge computing, integration with digital twins, long-term shipboard validation studies
Automatic Fault Detection & Real-Time Analysis	YOLO, U-Net, GAN augmentation, edge–cloud architectures	Enables real-time and autonomous fault recognition with high detection accuracy; robust for complex scenes	High reliance on synthetic/augmented data; generalization issues across vessels and equipment types	Development of benchmark maritime datasets; robust augmentation pipelines adapted to shipboard conditions
Environmental & Measurement Challenges	Environmental compensation models, emissivity correction	Humidity, salt particles, and temperature gradients identified as major sources of error; angular and distance-related measurement biases	Lack of maritime-specific correction standards; limited sensor ruggedization for the sea environment	Standardisation of correction models, sensor ruggedisation, geometry-aware inspection guidelines
Operational Implementation & Practical Challenges	Manual + AI-assisted inspection, semi-autonomous workflows	IRT increases safety, reduces inspection time, and provides actionable maintenance support	Cost, need for crew training, lack of IMO/ISO guidelines, insufficient classification society standards	Development of marine-grade protocols, training frameworks, unified guidelines for operational deployment

Although based on modern technologies, the analyzed studies share several limitations that reduce their applicability in real maritime industry conditions:

- Limited scope and representativeness of samples: most studies focus on individual components (bearings, motors) without including more complex systems such as cooling or power distribution systems on ships.

- Idealized testing conditions: many experiments are conducted in laboratories or simulation environments [23,24,35], without accounting for the effects of marine conditions (humidity, salt, vibrations, temperature shocks).
- Insufficient model validation: studies that use deep learning [23,26] rarely perform testing of models on independent real faults, making it difficult to assess their robustness and reliability.
- Technical limitations of sensors and calibration: many studies do not specify material emissivity, and some lack a detailed description of the sensor configuration, which can result in temperature measurement errors.
- Lack of time-series data and continuity of monitoring: analyses are mostly limited to instantaneous images rather than tracking changes over time, which is crucial for predictive maintenance.

These limitations highlight the gap between academic research and real-world maritime applications, where reliability, noise resistance, and scalability are crucial.

3.3. Technological Impact of Infrared Thermography

The results presented in Sections 3.1 and 3.2 provide a structured overview of the distribution, characteristics, and thematic orientation of the studies identified through the systematic search. However, because the included corpus predominantly reflects applied research carried out in maritime and industrial environments, certain fundamental aspects of infrared thermography, such as sensor characteristics, analytical approaches, and operational constraints, are only partially represented in these studies [8,11,20,21]. To support clearer interpretation of the systematic findings, this subsection integrates insights from both the reviewed papers and a set of established technological sources outlining the broader principles relevant to infrared imaging. This combined perspective enables a more comprehensive understanding of the capabilities, analytical methods, and limitations of infrared thermography in maritime applications, without altering the methodological integrity of the review.

Recent developments in infrared thermography have significantly influenced how the technology is applied in industrial and maritime systems. Most of the studies included in the present review, as well as recent industrial surveys, report the use of long-wave infrared (LWIR, 8–14 μm) cameras for condition monitoring and inspection tasks, owing to their robustness under variable lighting conditions and their suitability for machinery diagnostics [11,20]. Broader technological reviews note that mid-wave infrared (MWIR, 3–5 μm) systems offer higher sensitivity to small temperature gradients and elevated-temperature components, and can therefore be advantageous for inspecting exhaust systems, engine components, and thermally loaded structures [50,83]. The choice between cooled and uncooled detectors, differences in noise-equivalent temperature difference, optical design, and frame integration directly influence measurement accuracy and defect detectability, particularly in conditions where thermal contrasts are limited or where targets occupy only a small portion of the field of view [50,68,83]. Although the maritime studies surveyed in this review predominantly employ passive thermography, in which temperature distributions are recorded during regular operation [11,21], recent technological advances highlight substantial progress in active thermographic techniques, including pulsed thermography, lock-in thermography, modulated excitation, and thermal signal reconstruction, that enhance defect visibility and support the detection of subsurface anomalies [47,76,84]. Their limited representation in shipboard case studies, aside from isolated applications to marine structures [57], indicates a clear opportunity to expand methodological diversity in maritime thermographic diagnostics.

In terms of image analysis, most of the reviewed maritime studies rely on relatively simple processing strategies. Common approaches include threshold-based hotspot identification, extraction of maximum or mean temperatures from regions of interest, and basic segmentation or statistical descriptors used to distinguish normal from abnormal conditions [8,11,41,44]. While these methods are computationally efficient and straightforward to implement on board, their robustness is limited by variations in emissivity, reflective surfaces, ambient temperature fluctuations, and measurement geometry [68], or in other words, the applicability. More advanced data-reduction and signal-processing approaches, such as principal component thermography, singular value decomposition, and other multivariate decomposition techniques, have been shown to improve defect contrast and noise suppression in laboratory and structural applications [47,76,84], yet they appear only sporadically in maritime case studies. Parallel to these developments, there has been rapid growth in the use of machine learning and deep learning for automated interpretation of thermal images. Studies on rotating machinery, induction motors, and marine diesel engines demonstrate that convolutional neural networks, feature-learning architectures, and hybrid models can successfully extract fault-related thermal patterns and achieve high classification performance in controlled environments [17,36,55,58]. Nonetheless, the practical transition of these methods to shipboard use remains constrained by the scarcity of labelled datasets specific to maritime machinery, heterogeneity of equipment configurations across vessels, and the computational requirements associated with real-time inference under operational conditions [36,55].

Across both the systematic corpus and the extended technical sources, several practical limitations emerge as characteristic constraints for infrared thermography in maritime environments. Environmental influences, including high humidity, salt aerosols, surface contamination, radiative reflections, and rapid ambient temperature fluctuations, can degrade thermal contrast or introduce apparent anomalies, thereby complicating image interpretation [50,68,69,85]. In enclosed machinery spaces, i.e., engine rooms, elevated background temperatures, dense equipment layouts, and the presence of polished metallic surfaces, together with ever-present vibrations, further increase measurement uncertainty and require careful adjustment of emissivity settings, viewing angles, and measurement distances [11,21,68]. From an operational perspective, reviews of infrared thermography within condition-based monitoring and predictive maintenance highlight that the cost of high-performance cameras, the need for specialized training, and the absence of sector-specific procedures continue to act as barriers to widespread adoption, particularly in industries such as maritime transport, where maintenance practices vary across vessel types and operators [13,15,63]. For this reason, infrared thermography is often deployed as one component within broader diagnostic frameworks, complementing vibration analysis, electrical measurements, and other condition-based techniques rather than functioning as a standalone tool [13,15]. Taken together, these technological, analytical, and organizational factors help explain why infrared thermography, despite its demonstrated value and its growing relevance in industrial monitoring, remains only partially integrated into routine inspection and maintenance practices in the maritime domain [20,50,83].

3.4. Summary of Findings and Implications for Future Research

The conducted review revealed a coherent research trend toward the digital transformation of thermographic diagnostics in the maritime sector. Rather than focusing on individual case studies, recent publications increasingly approach infrared thermography (IRT) as part of integrated data-driven maintenance frameworks. This evolution reflects a shift from purely thermal measurements to intelligent diagnostic systems that combine IRT with artificial intelligence, machine learning, and advanced sensor networks.

The findings indicate that contemporary research prioritizes automation, early fault detection, and the optimization of maintenance procedures for critical ship components. Despite notable methodological advancements, the literature remains fragmented by limited experimental validation and the dominance of laboratory-based testing over real operational conditions. Papers on system reliability, cost-effectiveness, and large-scale data fusion remain scarce, underscoring the need for stronger interdisciplinary collaboration among mechanical, electrical, and computer engineers.

The analysis further reveals several recurring research gaps, including limited real-ship validation, insufficient standardization of thermographic measurement procedures, a lack of large annotated datasets, and minimal attention to calibration, emissivity correction, and environmental influences on measurement accuracy. These findings confirm that existing ISO and IEC standards do not fully account for shipboard environmental variability, such as humidity, fluctuating thermal loads, and reflective metal surfaces, which complicates accurate calibration and emissivity estimation in maritime settings.

To overcome the limitations identified in this review and to support the practical implementation of IRT-based diagnostics in the maritime sector, several research priorities should be addressed. Future work should focus on developing unified maritime-specific standards and validation protocols for IRT-AI systems, including emissivity guidelines for typical ship components and calibration procedures adapted to high-humidity, highly reflective engine-room environments.

Expanding long-term thermographic datasets collected under varying operational and environmental conditions will be crucial for improving the robustness, generalizability, and explainability of diagnostic models. Further progress depends on integrating thermography with complementary diagnostic modalities, such as vibration, acoustic, and ultrasonic analysis, enabling multimodal, hybrid fault-diagnosis frameworks that can capture complex early-stage anomalies.

Additionally, future studies should be conducted to evaluate the long-term economic, safety, and reliability impacts of IRT-based predictive maintenance strategies to quantify their contribution to optimized ship operations and reduced downtime. Promising research directions also include integrating infrared thermography with digital twins, edge-cloud computing architectures, and IoT sensor networks to enable real-time, scalable, and data-efficient diagnostic systems.

Finally, the development of user-oriented onboard tools, such as automated reporting dashboards, intuitive visualization interfaces, and tailored training modules, could be essential to facilitate operational adoption of thermography-enhanced maintenance procedures and to ensure their alignment with IMO decarbonization targets and emerging maritime safety regulations.

4. Conclusions

This systematic review analyzed 210 publications retrieved from Web of Science, Scopus, and Google Scholar, of which 40 met the inclusion criteria, utilizing the PRISMA 2020 methodology. The quantitative assessment confirms a steady growth of scientific interest over the past decade, with research activity peaking in 2023–2024. Thus, the upward trend reflects the broader shift toward digital and intelligent maintenance technologies within the maritime sector.

The findings confirm the hypothesis that infrared thermography (IRT) is an effective proactive diagnostic tool that significantly reduces unplanned downtime and lowers maintenance costs compared to traditional reactive approaches. Across the reviewed studies, IRT consistently demonstrated strong performance in detecting overheating, insulation

degradation, and faulty electrical connections, factors that directly influence the operational safety and reliability of ship systems.

However, several limitations and research gaps were identified. A substantial number of studies were conducted under controlled laboratory conditions rather than in real maritime environments, highlighting a lack of operational data at sea. Many papers focus exclusively on terrestrial applications of IRT, making shipboard implementations more challenging due to unique environmental and operational constraints. Furthermore, the limited availability of datasets for training AI-assisted thermographic models complicates the deployment of edge–cloud predictive maintenance architectures. To address these data limitations, GANs can be employed to synthesize realistic thermal images of shipboard faults, enhancing AI model training and improving diagnostic accuracy. Existing ISO and IEC standards were also found to provide insufficient guidance for measurement accuracy in the specific environmental conditions of ships, such as variable humidity, reflective metal surfaces, and fluctuating thermal loads.

Overall, this review provides the most up-to-date synthesis of research on infrared thermography in maritime applications, highlighting both the technological potential and the existing limitations of current approaches. The collective evidence demonstrates that infrared thermography represents a mature, reliable, and non-destructive diagnostic technique whose systematic integration into maintenance strategies could strengthen the safety, efficiency, and sustainability of maritime operations.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app152312551/s1>, File S1: PRISMA 2020 Checklist. Open Science Framework Registration: https://osf.io/2y3he/overview?view_only=5577e3fad2ab4f83ac1a01c6a9f016f2, accessed on 29 October 2025. Open Science Framework Project: https://osf.io/c6as9/overview?view_only=6970a7a018104b028056f2b855736c91, accessed on 29 October 2025.

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Abbreviations

The following abbreviations are used in this manuscript:

IRT	Infrared thermography
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
WoS	Web of Science
AI	Artificial intelligence
DL	Deep learning
CNN	Convolutional neural network
GHG	Greenhouse gas
SOLAS	International Convention for Safety of Life at Sea

MARPOL	International Convention for the Prevention of Pollution from Ships
CBM	Condition-based maintenance
PrM	Predictive maintenance
ML	Machine learning
LNG	Liquefied natural gas
LPG	Liquefied petroleum gas
GAN	Generative adversarial network
IoT	Internet of Things
IEEE	Institute of Electrical and Electronics Engineers
MDPI	Multidisciplinary Digital Publishing Institute
cGAN	Conditional generative adversarial network
YOLOv8	You Only Look Once version 8
BoVW	Bag of Visual Words
IR	Infrared (radiation)
SVM	Support vector machine
RF	Radio frequency
IMO	International Maritime Organization
OSF	Open Science Framework
ISO	International Organization for Standardization
IEC	International Electrotechnical Commission
NDT	Non-destructive testing

References

- Butrymowicz, D.; Zieliński, T.; Kędzierski, M.; Gagan, J.; Lukaszuk, M.; Śmierciew, K.; Pawluczuk, A. Experimental validation of new approach for waste heat recovery from combustion engine for cooling and heating demands from combustion engine for maritime applications. *J. Clean. Prod.* **2021**, *290*, 125206. [\[CrossRef\]](#)
- IMO 2020–Cutting Sulphur Oxide Emissions. Available online: <https://www.imo.org/en/mediacentre/hottopics/pages/sulphur-2020.aspx> (accessed on 18 November 2025).
- European Commission Brussels. Commission Publishes First Annual EU Report on CO₂ Emissions from Maritime Transport. Available online: https://ec.europa.eu/clima/news-your-voice/news/commission-publishes-first-annual-eu-report-co2-emissions-maritime-transport-2020-05-25_en (accessed on 17 November 2025).
- 2023 IMO Strategy on Reduction of GHG Emissions from Ships. Available online: <https://www.imo.org/en/ourwork/environment/pages/2023-imo-strategy-on-reduction-of-ghg-emissions-from-ships.aspx> (accessed on 18 November 2025).
- ISO 18434-1:2008; Condition Monitoring and Diagnostics and Diagnostics of Machines–Thermography Part 1: General Procedures. ISO: Geneva, Switzerland, 2008. Available online: <https://www.iso.org/standard/41648.html> (accessed on 18 November 2025).
- ISO 9288:2022; Thermal Insulation–Heat Transfer by Radiation–Vocabulary. ISO: Geneva, Switzerland, 2022. Available online: <https://www.iso.org/obp/ui/#iso:std:iso:9288:en/> (accessed on 18 November 2025).
- IEC TS 62492-1:2008; Industrial Process Control Devices–Radiation Thermometers–Part 1: Technical Data for Radiation Thermometers. iTeh Standards: San Francisco, CA, USA, 2008. Available online: <https://webstore.iec.ch/en/publication/7103/> (accessed on 18 November 2025).
- Venegas, P.; Ivorra, E.; Ortega, M.; Saez de Ocariz, I. Towards the Automation of Infrared Thermography Inspection for Industrial Maintenance Applications. *Sensors* **2022**, *22*, 613. [\[CrossRef\]](#) [\[PubMed\]](#)
- Ortega, M.; Ivorra, E.; Juan, A.; Venegas, P.; Martinez, J.; Alcaniz, M. MANTRA: AN Effective System Based on Augmented Reality and Infrared Thermography for Industrial Maintenance. *Appl. Sci.* **2021**, *11*, 385. [\[CrossRef\]](#)
- Melnyk, O.; Onyschchenko, S.; Onishchenko, O.; Lohinov, O.; Ocheretna, V. Integral Approach to Vulnerability Assessment of Ship’s Critical Equipment and Systems. *Trans. Marit. Sci.* **2023**, *12*. [\[CrossRef\]](#)
- Krystosik-Gromadzińska, A. Affordable hybrid thermography for merchant vessel engine room fire safety. *Sci. J. Marit. Univ. Szczec.* **2019**, *21*–26. [\[CrossRef\]](#)
- Karatug, C.; Arslanoglu, Y.; Soares, G. Review of maintenance strategies for ship machinery systems. *J. Mar. Eng. Technol.* **2023**, *22*, 233–247. [\[CrossRef\]](#)
- Balakrishnan, G.K.; Yaw, C.T.; Koh, S.P.; Abedin, T.; Raj, A.A.; Tiong, S.K.; Chen, C.P. A Review of Infrared Thermography for Condition-Based Monitoring in Electrical Energy: Applications and Recommendations. *Energies* **2022**, *15*, 6000. [\[CrossRef\]](#)

14. Godoy, D.R.; Mavrakakis, C.; Mena, R.; Kristjanpoller, F.; Viveros, P. An Advanced Framework for Predictive Maintenance Decisions: Integrating the Proportional Hazards Model and Machine Learning Techniques under CBM Multi-Covariate Scenarios. *Appl. Sci.* **2024**, *14*, 5514. [\[CrossRef\]](#)
15. Ali, A.; Abdelhadi, A. Condition-Based Monitoring and Maintenance: State of the Art Review. *Appl. Sci.* **2022**, *12*, 688. [\[CrossRef\]](#)
16. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Appl. Sci.* **2022**, *12*, 8081. [\[CrossRef\]](#)
17. Ullah, I.; Yang, F.; Khan, R.; Liu, L.; Yang, H.; Gao, B.; Sun, K. Predictive Maintenance of Power Substation Equipment by Infrared Thermography Using a Machine-Learning Approach. *Energies* **2017**, *10*, 1987. [\[CrossRef\]](#)
18. Trejo-Chavez, O.; Cruz-Albarran, I.A.; Resendiz Ochoa, E.; Salinas-Aguilar, A.; Morales-Hernandez, L.; Basurto-Hurtado, J.A.; Perez-Ramirez, C.A. A CNN-Based Methodology for Identifying Mechanical Faults in Induction Motors Using Thermography. *Machines* **2023**, *11*, 752.
19. Lu, D.; Tang, H.; Teng, L.; Tan, J.; Wang, M.; Tian, Z.; Wang, L. Multiscale Feature-Based Infrared Ship Detection. *Appl. Sci.* **2024**, *14*, 246. [\[CrossRef\]](#)
20. Osornio-Rios, A.; Antonino-Daviu, J.; Romero-Troncoso, R.J. Recent industrial applications of infrared thermography: A review. *IEEE Trans. Ind. Inform.* **2019**, *15*, 615–625. [\[CrossRef\]](#)
21. Monieta, J. The use of thermography in the diagnosis of ship piston internal combustion engines, MATEC Web of Conferences. In Proceedings of the 17th International Conference Diagnostics of Machines and Vehicles, Les Ulis, France, 30 July 2018.
22. Lopez-Perez, D.; Antonino-Daviu, J. Detection of mechanical faults in induction machines with infrared thermography: Field cases. In Proceedings of the IECON 2016—42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016; pp. 7107–7112.
23. Li, Y.; Du, X.; Wan, F.; Wang, X.; Yu, H. Rotating machinery fault diagnosis based on convolutional neural network and infrared thermal imaging. *Chin. J. Aeronaut.* **2020**, *33*, 427–438. [\[CrossRef\]](#)
24. Wang, X.; Si, S.; Li, Y.; Li, Y. A fault diagnosis method for rotating machinery under variable speed condition based on infrared thermography. In Proceedings of the 2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), Xi'an, China, 15–17 August 2018; pp. 30–34.
25. Resendiz-Ochoa, E.; Morales-Hernandez, L.A.; Cruz-Albarran, I.A.; Alvarez-Junco, S. Induction Motor Failure Analysis using Machine Learning and Infrared Thermography. In Proceedings of the 2022 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 9–11 November 2022; pp. 1–6.
26. Wang, R.; Jia, X.; Liu, Z.; Dong, E.; Li, S.; Cheng, Z. Conditional generative adversarial network based data augmentation for fault diagnosis of diesel engines applied with infrared thermography and deep convolutional neural network. *Eksplot. I Niezawodn.* **2024**, *26*, 175291. [\[CrossRef\]](#)
27. Page, M.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [\[CrossRef\]](#)
28. Bojić, F.; Gudelj, A.; Bošnjak, R. Port-Related Shipping Gas Emissions—A Systematic Review of Research. *Appl. Sci.* **2022**, *12*, 3603. [\[CrossRef\]](#)
29. Karin, I.; Golub Medvešek, I.; Šoda, J. Best-Suited Communication Technology for Maritime Signaling Facilities: A Literature Review. *Appl. Sci.* **2025**, *15*, 3452. [\[CrossRef\]](#)
30. Munim, Z.H.; Dushenko, M.; Jimenza, V.J.; Shakil, M.H.; Imset, M. Big data and artificial intelligence in the maritime industry: A bibliometric review and future research directions. *Marit. Policy Manag.* **2020**, *47*, 577–597. [\[CrossRef\]](#)
31. Ferrarini, L.; Filippopoulos, Y.; and Lajic, Z. Digital Transformation in the Shipping Industry: A Network-Based Bibliometric Analysis. *J. Mar. Sci. Eng.* **2025**, *13*, 894. [\[CrossRef\]](#)
32. Delgado-Prieto, M.; Carino-Corrales, J.; Saucedo-Dorantes, J.J.; Romero-Troncoso, R.J.; Osornio-Rios, R.A. Thermography-Based Methodology for Multifault Diagnosis on Kinematic Chain. *IEEE Trans. Ind. Inform.* **2018**, *14*, 5553–5562. [\[CrossRef\]](#)
33. Fu, L.; Ma, Z.; Wang, Y.; Zhang, L. IRTCog: Fault Diagnosis of Rotor-Bearing System Based on Modified Transfer Model With Variable Visual Angle Thermal Images. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–11. [\[CrossRef\]](#)
34. Guan, X.; Gao, W.; Peng, H.; Shu, N.; Gao, D.W. Image-based incipient fault classification of electrical substation equipment by transfer learning of deep convolutional neural network. *IEEE Can. J. Electr. Comput. Eng. (CJECE)* **2022**, *45*, 1–8. [\[CrossRef\]](#)
35. Gugaliya, A.; Singh, G.; Naikan, V.N.A. Effective combination of motor fault diagnosis techniques. In Proceedings of the International Conference on Power, Instrumentation Control and Computing (PICC), Thrissur, India, 18–20 January 2018; pp. 1–5.
36. Jia, Z.; Liu, Z.; Vong, C.; Pecht, M. A Rotating Machinery Fault Diagnosis Method Based on Feature Learning of Thermal Images. *IEEE Access* **2019**, *7*, 12348–12359. [\[CrossRef\]](#)
37. Lopez-Perez, D.; Antonino-Daviu, J. Application of infrared thermography to fault detection in industrial induction motors: Case stories. In Proceedings of the 2016 XXII International Conference on Electrical Machines (ICEM), Lausanne, Switzerland, 4–7 September 2016; pp. 2172–2177.

38. Malyk, B.; Malyk-Zamorii, S. Thermography Testing of Telecommunication Facilities Temperature Conditions. In Proceedings of the 2017 4th International Scientific-Practical Conference Problems of Infocommunications. Science and Technology (PIC S&T), Kharkov, Ukraine, 10–13 October 2017; pp. 482–484.
39. Mechkov, E. Application of Infrared Thermography Technique in Transformers Maintenance in Distribution Network. In Proceedings of the 2017 15th International Conference on Electrical Machines, Drives and Power Systems (ELMA), Sofia, Bulgaria, 1–3 June 2017; pp. 354–357.
40. Mian, T.; Choudhary, A.; Fatima, S. Multi-Sensor Fault Diagnosis for Misalignment and Unbalance Detection Using Machine Learning. *IEEE Trans. Ind. Appl.* **2023**, *59*, 5749–5759. [\[CrossRef\]](#)
41. Ramirez-Nunez, J.A.; Morales-Hernandez, L.A.; Osornio-Rios, R.A.; Antonino-Daviu, J.A.; Romero-Troncoso, R.J. Self-adjustment Methodology of a Thermal Camera for Detecting Faults in Industrial Machinery. In Proceedings of the IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016.
42. Redon, P.; Romero-Troncoso, R.J.; Picazo-Rodenas, M.J.; Antonino-Daviu, J. Reliable methodology for online fault diagnosis in induction motors using passive infrared thermography. In Proceedings of the 2017 IEEE 11th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), Tinos, Greece, 29 August–1 September 2017.
43. Resendiz-Ochoa, E.; Enriquez-Ugalde, J.M.; Saucedo-Dorantes, J.J.; Morales-Hernandez, L.A. Broken Rotor Bar Failures Diagnosis with Supervised Learning and Infrared Thermography. In Proceedings of the 2021 IEEE 13th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), Dallas, TX, USA, 22–25 August 2021.
44. Resendiz-Ochoa, E.; Osornio-Rios, R.A.; Benitez-Rangel, J.P.; Morales-Hernandez, L.A.; Romero-Troncoso, R.J. Segmentation in Thermography Images for Bearing Defect Analysis in Induction Motors. In Proceedings of the 2017 IEEE 11th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED), Tinos, Greece, 29 August–1 September 2017.
45. Chen, Y.; Jhong, S.; Tu, S.; Lin, Y.; Wu, Y. Autonomous Smart-Edge Fault Diagnostics via Edge-Cloud-Orchestrated Collaborative Computing for Infrared Electrical Equipment Images. *IEEE Sens. J.* **2024**, *24*, 24630–24648. [\[CrossRef\]](#)
46. Choudhary, A.; Mian, T.; Fatima, S.; Panigrahi, B.K. Passive Thermography Based Bearing Fault Diagnosis Using Transfer Learning With Varying Working Conditions. *IEEE Sens.* **2023**, *23*, 4628–4637. [\[CrossRef\]](#)
47. Choung, Y.; Lee, S.; Kim, W. Latest advances in common signal processing of pulsed thermography for enhanced detectability: A review. *Appl. Sci.* **2021**, *11*, 12168. [\[CrossRef\]](#)
48. Fanchiang, K.; Huang, Y.; Kuo, C. Power Electric Transformer Fault Diagnosis Based on Infrared Thermal Images Using Wasserstein Generative Adversarial Networks and Deep Learning Classifier. *Electronics* **2021**, *10*, 1161. [\[CrossRef\]](#)
49. Guo, Y.; Zhang, Y.; Sun, B.; Wang, Y. Adversarial deep transfer learning in fault diagnosis: Progress, challenges, and future prospects. *Sensors* **2023**, *23*, 7263. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Hou, F.; Zhang, Y.; Zhou, Y.; Zhang, M.; Wu, J. Review on infrared imaging technology. *Sustainability* **2022**, *14*, 11161. [\[CrossRef\]](#)
51. Li, K.; Tian, G.Y.; Ahmed, J. Emissivity Correction and Thermal Pattern Reconstruction in Eddy Current Pulsed Thermograph. *Sensors* **2023**, *23*, 2646. [\[CrossRef\]](#)
52. Ucar, A.; Karakose, M.; Kirimca, N. Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Appl. Sci.* **2024**, *14*, 898. [\[CrossRef\]](#)
53. Gyung-Il, L.; Jae-Yeol, K. Evaluation of Reliability of Large Hybrid Curvic Gear Using Thermography. *Korean Soc. Manuf. Process Eng.* **2017**, *16*, 501–759.
54. Li, Y.; Wang, X.; Si, S.; Du, X. A New Intelligent Fault Diagnosis Method of Rotating Machinery under Varying-Speed Conditions Using Infrared Thermography. *Complexity* **2019**, *2019*, 1076–2787. [\[CrossRef\]](#)
55. Mian, T.; Choudhary, A.; Fatima, S. Vibration and infrared thermography based multiple fault diagnosis of bearing using deep learning. *Nondestruct. Test. Eval.* **2022**, *38*, 275–296. [\[CrossRef\]](#)
56. Pang, J.; Yu, Z.; Chen, X. Research on thermal imaging fault detection system based on Weibull distributed electrical system. *J. Phys. Conf. Ser.* **2021**, *1941*, 012037. [\[CrossRef\]](#)
57. Świdorski, W. Possibility of defect detection by eddy current thermography in marine structures. *Sci. J. Marit. Univ. Szczec.* **2015**, *44*, 355–370.
58. Wang, R.; Yan, H.; Dong, E.; Cheng, Z.; Li, Y.; Jia, X. Infrared thermography based fault diagnosis of diesel engines using convolutional neural network and image enhancement. *Open Phys.* **2024**, *22*, 20240110. [\[CrossRef\]](#)
59. Goel, A.K.; Naikan, V.N.A. Exploring the Diagnostic Potential of Infrared Thermography for Experimental Assessment of Cavitation and Air Entrainment-induced Faults in Centrifugal Pumps. *J. Appl. Fluid Mech.* **2024**, *17*, 352–369. [\[CrossRef\]](#)
60. Oldfield, M.; McMonies, M.; Haig, E. The future of condition based monitoring: Risks of operator removal on complex platforms. *AI Soc.* **2024**, *39*, 465–476. [\[CrossRef\]](#)
61. Bampoula, X.; Nikolakis, N.; Alexopoulos, K. Condition Monitoring and Predictive Maintenance of Assets in Manufacturing Using LSTM-Autoencoders and Transformer Encoders. *Sensors* **2024**, *24*, 3215. [\[CrossRef\]](#) [\[PubMed\]](#)

62. Garcia, J.; Rios-Colque, L.; Pena, A.; Rojas, L. Condition Monitoring and Predictive Maintenance in Industrial Equipment: An NLP-Assisted Review of Signal Processing, Hybrid Models, and Implementation Challenges. *Appl. Sci.* **2025**, *15*, 5465. [\[CrossRef\]](#)
63. Moleda, M.; Malysiak-Mrozek, B.; Ding, W.; Sunderam, V.; Mrozek, D. From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry. *Sensors* **2023**, *23*, 5970. [\[CrossRef\]](#) [\[PubMed\]](#)
64. Riccio, C.; Menanno, M.; Zennaro, I.; Savino, M.M. A New Methodological Framework for Optimizing Predictive Maintenance Using Machine Learning Combined with Product Quality Parameters. *Machines* **2024**, *12*, 443. [\[CrossRef\]](#)
65. Briguglio, G.; Crupi, V. Review on Sensors for Sustainable and Safe Maritime Mobility. *J. Mar. Sci. Eng.* **2024**, *12*, 353. [\[CrossRef\]](#)
66. Maione, F.; Lino, P.; Maione, G.; Giannino, G. A Machine Learning Framework for Condition-Based Maintenance of Marine Diesel Engines: A Case Study. *Algorithms* **2024**, *17*, 411. [\[CrossRef\]](#)
67. Sutherland, N.; Marsh, S.; Priestnall, G.; Bryan, P.; Mills, J. InfraRed Thermography and 3D- Data Fusion for Architectural Heritage: A Scoping Review. *Remote Sens.* **2023**, *15*, 2422. [\[CrossRef\]](#)
68. Pušnik, I.; Geršak, G. Evaluation of the Size-of-Source Effect in Thermal Imaging Cameras. *Sensors* **2021**, *21*, 607. [\[CrossRef\]](#)
69. Gallardo-Saavedra, S.; Hernandez-Callejo, L.; del Carmen Alonso-Garcia, M.; Munoz-Cruzado-Alba, J.; Ballestin-Fuertes, J. Infrared Thermography for the Detection and Characterization of Photovoltaic Defects: Comparison between Illumination and Dark Conditions. *Sensors* **2020**, *20*, 4395. [\[CrossRef\]](#)
70. Loche, M.; Scaringi, G.; Blahut, J.; Hartvich, F. Investigating the Potential of Infrared Thermography to Inform on Physical and Mechanical Properties of Soils for Geotechnical Engineering. *Remote Sens.* **2022**, *14*, 4067.
71. Alvarado-Hernandez, A.I.; Zamudio-Ramirez, I.; Jean-Cuellar, A.Y.; Osornio-Rios, R.A.; Donderis-Quiles, V.; Antonino-Daviu, J.A. Infrared Thermography Smart Sensor for the Condition Monitoring of Gearbox and Bearing Faults in Induction Motors. *Sensors* **2022**, *22*, 6075. [\[CrossRef\]](#) [\[PubMed\]](#)
72. Qureshi, U.R.; Rashid, A.; Altini, N.; Bevilacqua, V.; La Scala, M. Radiometric Infrared Thermography of Solar Photovoltaic Systems: An Explainable Predictive Maintenance Approach for Remote Aerial Diagnostic Monitoring. *Smart Cities* **2024**, *7*, 1261–1288. [\[CrossRef\]](#)
73. Angrisani, L.; De Benedetto, E.; Duraccio, L.; Lo Regio, F.; Ruggiero, R.; Tedesco, A. Infrared Thermography for Real-Time Assessment of the Effectiveness of Scoliosis Braces. *Sensors* **2023**, *23*, 8037. [\[CrossRef\]](#) [\[PubMed\]](#)
74. Korelidou, V.; Simitzis, P.; Massouras, T.; Gelasakis, A.I. Infrared Thermography as a Diagnostic Tool for the Assessment of Mastitis in Dairy Ruminants. *Animals* **2024**, *14*, 2691. [\[CrossRef\]](#)
75. Ma, Y.; Vien, B.S.; Kuen, T.; Chiu, W.K. Clustering-Based Thermography for Detecting Multiple Substances Under Large-Scale Floating Covers. *Sensors* **2024**, *24*, 8030. [\[CrossRef\]](#)
76. Ebrahimi, S.; Fleuret, J.; Klein, M.; Therodux, L.-D.; Georges, M.; Ibarra-Castanedo, C.; Maldaque, X. Robust Principal Component Thermography for Defect Detection in Composites. *Sensors* **2021**, *21*, 2682. [\[CrossRef\]](#)
77. Wei, Z.; Fernandes, H.; Herrmann, H.-G.; Tarpani, J.R.; Osman, A. A Deep Learning Method for the Impact Damage Segmentation of Curve-Shaped CFRP Specimens Inspected by Infrared Thermography. *Sensors* **2021**, *21*, 395. [\[CrossRef\]](#)
78. Cabizosu, A.; Grotto, D.; Lopez Lopez, A.; Castaneda Vozmediano, R. Thermography Sensor to Assess Motor and Sensitive Neuromuscular Sequels of Brain Damage. *Sensors* **2024**, *24*, 1723. [\[CrossRef\]](#)
79. Alves, R.; van Meulen, F.; Overeem, S.; Zinger, S.; Stuijk, S. Thermal Cameras for Continuous and Contactless Respiration Monitoring. *Sensors* **2024**, *24*, 8118. [\[CrossRef\]](#) [\[PubMed\]](#)
80. Faus Camarena, M.; Izquierdo-Renau, M.; Julian-Rochina, I.; Arrebola, M.; Miralles, M. Update on the Use of Infrared Thermography in the Early Detection of Diabetic Foot Complications: A Bibliographic Review. *Sensors* **2024**, *24*, 252. [\[CrossRef\]](#)
81. Applied Sciences Special Issue: Recent Progress in Infrared Thermography. 2023. Available online: https://www.mdpi.com/journal/applsci/special_issues/8H48M7D458 (accessed on 19 October 2025).
82. Special Issue/Topical Collection: Big Data and AI Approaches for Infrared Thermography Inspection. 2022. Available online: https://www.mdpi.com/journal/applsci/special_issues/Infrared_Inspection (accessed on 22 October 2025).
83. Vollmer, M.; Möllmann, K.-P. *Infrared Thermal Imaging Fundamentals, Research and Applications*; Wiley: Hoboken, NJ, USA, 2010; ISBN 978-3-527-40717-0.
84. Hidayat, Z.; Avdelidis, N.P.; Fernandes, H. Brief Review of Vibrothermography and Optical Thermography for Defect Quantification in CFRP Material. *Sensors* **2025**, *25*, 1847. [\[CrossRef\]](#) [\[PubMed\]](#)
85. Perez-Ema, N.; Alvarez de Buergo, M.; Gomez-Heras, M. Monitoring changes in hydric properties of treated stone material with conservation products by time-sequential IR thermography. *Archeol. Anthropol. Sci.* **2024**, *16*, 1–15. [\[CrossRef\]](#)

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