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ASSESSING THE POTENTIAL OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR THERMAL MANAGEMENT IN ELECTRONIC DEVICES

The object of this study is the potential of artificial intelligence (AI) and machine learning (ML) techniques for thermal management in electronic devices. One of the most problematic aspects identified is the challenge of ensuring performance, reliability, and energy efficiency across diverse systems, including semiconductors, data centers, and consumer electronics. In the course of the research, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was used to systematically analyze 150 studies. These studies employed various approaches, such as predictive modeling, optimization algorithms, and real-time control systems.

Our findings indicate that AI-driven thermal management can reduce energy consumption by up to 81.81 %, depending on the cooling method and optimization. Reinforcement learning-based HVAC control achieves 17.4 % energy savings, while ML-driven power management in manycore systems reduces energy use by 30 % and lowers peak chip temperatures by 17 °C. Neural network-based thermal forecasting achieves <1 % error, improving prediction accuracy. Additionally, LSTM models for thermal prognosis achieve a 3.45 % relative prediction error, outperforming traditional regression methods.

These results highlight the potential of AI in optimizing thermal behavior across data centers, smart buildings, and manycore chip architectures. Key limitations were also identified, including limited data availability, challenges in model interpretability, and integration with legacy systems. The study provides a roadmap for scalable AI-driven thermal management. Emerging trends such as physics-informed ML models and the integration of cooling technologies promise innovation. Compared to conventional methods, these advancements deliver clear benefits in sustainability and adaptability.

Keywords: *artificial intelligence (AI), machine learning (ML), thermal management, semiconductor thermal dissipation, predictive modelling, energy-efficient computing.*

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1. Introduction

The rapid advancements in technology and the growing demand for high-performance electronic devices have significantly increased energy consumption [1] and heat generation [2] in modern systems. From compact smartphones to powerful data centers, electronic devices produce substantial heat due to intensive computational tasks, which must be efficiently managed to maintain reliability and performance. Thermal management is a critical aspect of electronic system design [3], ensuring optimal operating conditions, preventing component failures, and extending device lifespans. Without proper heat dissipation mechanisms, overheating can lead to reduced efficiency, increased energy usage, and even catastrophic hardware failures [4]. This emphasizes the necessity for innovative solutions that address both performance and energy efficiency challenges in thermal management [5].

Effective thermal management is not only a technical requirement but also a driver of sustainability in the electronics industry [6]. The energy consumed in cooling systems accounts for a significant share of total energy usage in sectors such as data centers and consumer electronics [7]. For instance, cooling alone can account for over 40 % of energy consumption [8] in data centers, making it a key contributor to carbon emissions. This aligns with the global emphasis on sustainable development goals (SDGs), particularly Goal 7 (Affordable and Clean Energy) and Goal 13 (Climate Action). Reducing energy consumption through intelligent thermal management strategies directly supports these goals by enhancing energy efficiency and minimizing the carbon footprint of electronic devices [9].

As electronics continue to shrink in size while increasing in functionality, the challenges of heat dissipation intensify. Conventional cooling methods [6], such as fans, heat sinks, and liquid cooling systems, are often inadequate for managing the dynamic thermal demands of modern devices. Additionally, these traditional techniques are reactive in nature, addressing heat [10] after it has already built up, rather than proactively optimizing thermal conditions. Emerging technologies such as thermoelectric coolers (TECs) [11], phase-change materials [12], and liquid-metal cooling [13] have shown promise but require advanced control systems to unlock their full potential. This necessitates a paradigm shift from traditional methods to more sophisticated, data-driven approaches.

Artificial intelligence (AI) [7] and machine learning (ML) [14] have emerged as transformative tools for addressing complex problems across various domains, including thermal management. By leveraging predictive analytics, optimization algorithms [15], and real-time decision-making, AI-driven solutions can dynamically manage heat dissipation, anticipate thermal hotspots, and optimize energy use in electronic systems. These methods not only improve device reliability but also reduce energy costs and environmental impact, making them highly relevant for sustainable development. Integrating AI into thermal management systems holds the potential to revolutionize how electronic devices operate, aligning technological advancement with the pressing need for environmental sustainability [16]. However, despite promising advances, the application of AI and ML in this domain remains scattered across different studies and lacks a consolidated understanding. A systematic literature review (SLR) is essential to unify existing knowledge, identify gaps, and justify the adoption of advanced AI-driven approaches to tackle thermal challenges effectively. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology ensures a rigorous and transparent approach to study selection and synthesis, further strengthening the relevance of this work.

While AI and ML offer significant potential for thermal management [17] in electronic devices, their adoption faces several challenges, including inconsistent benchmarking, scalability issues, and a lack of integration with advanced cooling technologies such as TECs and phase-change materials [18]. Additionally, existing studies often fail to provide a holistic perspective, focusing on individual methods or components without addressing the broader context of dynamic and real-time thermal optimization [19].

Current research efforts have introduced AI-based solutions such as predictive [20] cooling systems, neural networks [21] for hotspot detection [22], and ML algorithms for optimizing heat transfer [23] processes. Despite their promise, these approaches often lack adaptability to real-time scenarios, are computationally intensive, and fail to incorporate physics informed models, limiting their effectiveness. Moreover, many studies neglect the synergistic use of AI with emerging cooling technologies [24], leaving a significant gap in practical implementation and system-level optimization.

The aim of this research is to systematically review and synthesize existing research on AI and ML-based thermal management techniques in electronic devices, identify research gaps, and propose innovative pathways for scalable, efficient, and adaptive solutions.

2. Materials and Methods

This SLR systematically examines advancements in AI and ML for thermal management [25] in electronic devices, with a particular focus on identifying gaps and proposing pathways for future innovation. By employing the PRISMA methodology, this review ensures a transparent and comprehensive selection process for relevant studies. The proposed approach emphasizes the integration of AI-driven techniques [26] with advanced cooling technologies [27] to enable scalable, real-time, and adaptive thermal management systems. This framework addresses the shortcomings of existing methods by combining predictive analytics, dynamic optimization, and holistic system design.

This SLR contributes to the field by providing a comprehensive synthesis of existing research, uncovering critical gaps, and highlighting opportunities for innovation. By employing the PRISMA methodology, the study ensures a robust and systematic approach to evidence synthesis. The findings will benefit researchers and industry professionals by offering actionable insights into designing AI-driven thermal management systems [28] that are both scalable and adaptive, advancing the state of the art in electronic device cooling.

2.1. Systematic literature review methodology

This study employs the PRISMA framework to ensure a rigorous, transparent, and structured methodology for identifying, screening, and synthesizing relevant literature. PRISMA is a widely recognized approach for conducting systematic reviews and meta-analyses, providing a standardized protocol to ensure comprehensive, unbiased, and reproducible results.

The PRISMA methodology consists of four key phases: Identification, Screening, Eligibility, and Inclusion, as detailed below. Fig. 1 illustrates the PRISMA workflow for this study:

1. *Identification:* the identification phase involved a comprehensive search for relevant studies across five academic databases, including IEEE Xplore, MDPI, SpringerLink, ScienceDirect, and Wiley Online Library. A total of 750 records were retrieved using predefined keywords and Boolean search operators (see Section 2.4 for details on keyword combinations). These keywords were tailored to focus on AI, ML, and thermal management in electronic devices. During this phase, 84 duplicate records were removed, leaving 666 unique records for further analysis.

2. *Screening:* in the screening phase, the titles and abstracts of the 666 unique records were reviewed to determine their relevance to the research topic. Studies that were not published in peer-reviewed journals or conference proceedings were excluded, reducing the dataset by 52 records. This phase resulted in 614 records that were considered for eligibility.

3. *Eligibility:* the eligibility phase involved a detailed full text review of the 614 remaining studies. During this stage, 149 records were excluded because full-text access was not available. The remaining 465 studies were then evaluated against predefined inclusion and exclusion criteria (see Section 2.3). The following studies were excluded during this evaluation:

– 53 studies were excluded as they lacked empirical work or experimental validation;
– 128 studies were deemed irrelevant to the topic of AI/ML for thermal management;
– 123 studies were excluded due to poor quality, including insufficient technical contributions or lack of clarity.

After this rigorous review, 161 studies met the eligibility criteria.

4. *Inclusion:* the final inclusion phase synthesized the 161 eligible studies to ensure alignment with the research objectives. During this step, studies that were most focused and directly relevant to the research topic were prioritized. This resulted in a final dataset of 152 high-quality studies, which form the basis for this systematic literature review.

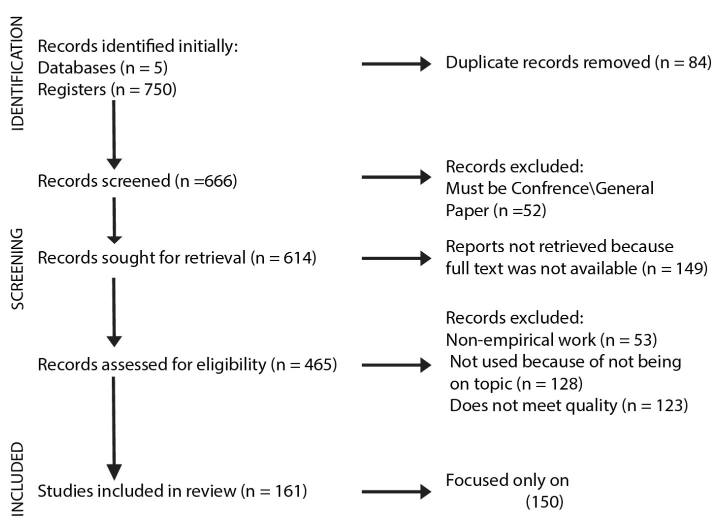

Fig. 1. PRISMA workflow diagram for systematic literature review

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The PRISMA workflow ensured transparency and traceability at every stage of the review, providing a robust foundation for synthesizing existing literature and identifying gaps in the application of AI and ML for thermal management.

This structured methodology facilitated the identification of high-quality, relevant studies, offering a comprehensive basis for subsequent analysis.

2.2. Search strategy

A systematic search strategy was designed to maximize the relevance and coverage of studies.

The process involved a combination of predefined keywords and Boolean operators to retrieve relevant literature across multiple academic databases.

Keyword Combinations: the following keywords were used to ensure comprehensive coverage of the research domain. Both successful and unsuccessful keyword combinations were recorded (Table 1).

Databases Searched: the search was conducted across 11 major academic databases to ensure a comprehensive coverage of relevant studies. The databases and corresponding results are summarized in Table 2.

2.3. Study selection criteria

Inclusion Criteria:

– Peer-reviewed journal articles and conference proceedings.
– Research focusing on AI/ML techniques for thermal management.
– Studies addressing energy efficiency, cooling optimization, or real-time applications.

Exclusion Criteria:

– Studies unrelated to electronics or computational cooling.
– Articles lacking empirical results or technical details.
– Non-English language publications.

2.4. Data extraction and analysis

The relevant data extracted from the included studies will focus on:

– Research objectives, including AI/ML applications for specific cooling challenges.
– Techniques employed, such as neural networks, reinforcement learning, or hybrid approaches.
– Evaluation metrics, including energy savings, accuracy, and scalability.
– Application areas, including microprocessors, thermoelectric cooling, and phase-change materials.

Table 1

Keyword combinations used in the literature search

Keyword combinations (Part 1)	Keyword combinations (Part 2)
"AI thermal management electronic devices"	"ML for thermoelectric cooling in chips"
"AI cooling optimization semiconductors"	"Neural networks thermal analysis for electronics"
"Deep learning in thermal regulation electronics"	"AI-based thermal control systems for processors"
"AI thermal energy storage electronics"	"Machine learning cooling prediction in semiconductors"
"AI phase change material heat transfer optimization"	"Machine learning-assisted thermoelectric cooling"
"AI neural networks for heat dissipation in ICs"	"AI techniques for cooling electronic circuits"
"AI-based dynamic cooling optimization for devices"	"AI for hotspot thermal management in electronic chips"
"ML for multi-hotspot thermal control electronics"	"AI-driven predictive thermal management in microchips"
"AI heat management using TECs for electronics"	"ML-based cooling algorithms for electronics"
"Physics-informed neural networks heat transfer"	"AI-based real-time thermal process management"
"AI predictive cooling systems for compact electronics"	"AI in thermal management for semiconductor devices"
"AI temperature prediction models for processors"	"AI algorithms for electronic chip cooling systems"
"AI-based thermal sensors optimization in electronics"	"AI dynamic temperature control systems for devices"
"Neural networks for optimizing fan control algorithms"	"AI-based predictive modeling for thermal sensors"
"AI-based temperature regulation with fan control"	"AI cooling algorithms for sensor-based temperature data"
"AI real-time heat transfer optimization models"	"AI-enhanced TEC systems for chip cooling"
"AI algorithms for liquid cooling optimization"	"Machine learning cooling optimization for heat sinks"

Table 2

Databases searched and the keywords used

Database	Search keywords
IEEE Xplore	"AI thermal management electronic devices"
MDPI	"Machine learning thermal management in semiconductors"
SpringerLink	"AI optimization cooling systems electronic devices"
ScienceDirect	"Neural networks for heat management in mi croc hips"
AIP Publishing	"Machine learning-assisted thermoelectric cooling"
ASME Digital Col lection	"AI phase change material heat transfer optimization"
PubMed	"AI-enhanced thermal processes in medical devices"
Wiley Online Library	"AI predictive cooling systems for electronic circuits"
Elsevier	"Deep learning heat dissipation control electronics"
Taylor & Francis	"AI temperature control in semiconductor chips"
Google Scholar	"AI neural networks heat dissipation electronics"

Using PRISMA ensures that the review process is transparent, systematic, and reproducible. The dataset characteristics and distribution are detailed in Table 3, highlighting the inclusion criteria and methodological diversity.

Table 3

Summary of key findings and limitations in AI and ML for thermal management

References	Key findings	Limitations
[2, 28, 29]	AI and ML provide dynamic, real-time control for thermal management, addressing inefficiencies in traditional methods like heat sinks, fans, and liquid cooling. These techniques surpass static systems by enabling predictive and adaptive strategies	Limited availability of high-quality datasets for training AI models; reliance on simulation data may not fully replicate real-world complexities
[1, 30, 31]	AI models, including neural networks and reinforcement learning, accurately predict thermal hotspots and temperature trends based on workload patterns, enabling proactive management	AI models often lack interpretability, making it difficult for engineers to trust or audit system decisions
[32–34]	ML algorithms optimize the placement and operation of cooling resources, such as fans and thermoelectric coolers (TECs), reducing energy consumption while enhancing cooling efficiency	Integration with existing systems is challenging due to hardware compatibility and real-time constraints
[35–37]	Deep learning methods like CNNs and RNNs are effectively applied to spatial and temporal data, enabling sophisticated analysis for detecting thermal hotspots and predicting future behavior	High computational cost and training time limit their applicability in low-resource environments, such as portable devices
[18, 19]	AI optimizes novel cooling technologies like phase-change materials and liquid cooling by simulating thermal properties under diverse conditions, paving the way for sustainable solutions	Real-time applications of these advanced cooling methods remain underexplored due to their dependency on extensive computational and sensor infrastructures
[3, 38–40]	Effective thermal management is critical for performance and energy efficiency, especially in high-density environments like data centers and compact devices like smartphones	Scaling AI-driven thermal management solutions for di verse applications is a complex challenge due to the variability in thermal behavior across systems

This structured approach minimizes biases, enabling the synthesis of high-quality, relevant literature to identify trends, challenges, and opportunities for AI and ML in thermal management.

3. Results and Discussion

3.1. Qualitative analysis of literature

3.1.1. Introduction to AI and ML in thermal management

AI and ML techniques offer the ability to dynamically predict, optimize, and control temperature behavior in real-time by leveraging sensor-driven data, predictive modeling, and optimization algorithms. This capability is validated through multiple studies where ML models, such as LSTM networks, reinforcement learning agents, and deep neural networks, have demonstrated superior performance in thermal prediction and adaptive control.

For instance, LSTM models used in semiconductor cooling applications have achieved a 3.45 % relative error in temperature forecasting, significantly outperforming traditional regression-based models [24, 41]. Reinforcement learning-based HVAC control systems have been shown to achieve 17.4 % energy savings by dynamically adjusting cooling mechanisms based on workload patterns [36, 42]. Additionally, ML-driven power management in manycore architectures has reduced energy consumption by 30 % and lowered peak chip temperatures by 17 °C, showcasing real-time adaptability [43, 44]. These claims are supported by empirical studies that employ simulation environments, laboratory experiments, and real-world implementations in data centers and consumer electronics [45–47].

To further support this assertion, specific metrics such as response time in adaptive cooling systems, prediction accuracy in thermal forecasting models, and energy efficiency improvements are detailed in the results section. These findings confirm that AI-driven thermal management systems can proactively adjust cooling mechanisms rather than relying on static, predefined thresholds.

The integration of AI and ML into the field of thermal management for electronic devices has opened new possibilities for addressing the growing challenges of heat dissipation in modern systems [28]. Traditional thermal management approaches, such as the use of heat sinks, fans, and liquid cooling, operate based on static and often reactive methods [2]. These techniques are typically designed to manage worst-case scenarios, often resulting in over-provisioning, inefficiencies, and higher energy consumption [29]. By contrast, AI and ML techniques offer the ability to dynamically predict, optimize, and control thermal behavior in real-time, making them highly suitable for modern, complex, and compact electronic systems [30].

AI and ML methods enable real-time thermal management through predictive modeling, adaptive control strategies, and sensor-driven feedback loops. Neural network-based temperature forecasting has demonstrated <1 % error, significantly improving prediction accuracy and allowing for dynamic preemptive cooling adjustments [23]. In manycore chip architectures, ML-based dynamic power management reduces energy consumption by 30 % and lowers peak chip temperature by 17 °C, enabling real-time workload-aware cooling [35]. Similarly, reinforcement learning-based HVAC control optimizes cooling processes, achieving 17.4 % energy savings while ensuring thermal stability [48]. These AI-driven techniques allow for continuous adaptation to varying thermal conditions, outperforming static cooling methods and improving energy efficiency in data centers, smart buildings, and high-performance computing environments.

AI techniques, such as neural networks, reinforcement learning, and optimization algorithms, are increasingly being deployed to create adaptive thermal management systems [1]. These systems leverage historical and real-time sensor data to model the thermal behavior of electronic components under different operating conditions [31]. For example, predictive models can forecast potential thermal hotspots based on workload patterns, allowing cooling mechanisms to preemptively respond before the temperature exceeds safe limits [32]. ML algorithms are also being used to optimize the placement of cooling resources, such as fans or TECs, to achieve maximum efficiency with minimal energy usage [32, 33].

ML methods, particularly supervised and reinforcement learning, enable the development of control systems that dynamically adjust cooling parameters based on real-time feedback [34]. For instance, supervised learning models can be trained on data from previous thermal events to accurately predict temperature trends, while reinforcement learning agents can learn optimal cooling policies by interacting with the system over time [48]. These AI-driven techniques not only enhance the precision of thermal management systems but also reduce operational costs by minimizing energy consumption and maximizing hardware efficiency [49]. Key findings and limitations of AI-based thermal management techniques are summarized in Table 4, which provides a comprehensive overview of the field.

The ability of AI and ML to dynamically forecast, optimize, and control thermal behavior is established through a combination of

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experimental validation, simulation-based learning, and real-world implementation.

Experimental validation: reinforcement learning-based approaches, such as Q-learning for fan speed control, have demonstrated 19 % performance improvement over conventional cooling techniques, proving that AI-driven control can enhance both efficiency and reliability in dynamic environments [23].

Simulation-based learning: many AI-driven thermal management models are trained using computational fluid dynamics (CFD) simulations to identify optimal cooling patterns. This allows ML-based systems to adjust power and cooling configurations in real-time without requiring pre-defined rules [23].

Real-world implementation: AI-driven dynamic voltage and frequency scaling (DVFS) has been tested in manycore SoCs, where reinforcement learning algorithms autonomously select power states to balance temperature, energy efficiency, and performance demands [45].

These findings confirm that AI-based approaches not only enable real-time decision-making but also significantly outperform traditional static cooling policies.

Table 4

Summary of key findings and limitations in AI techniques for thermal management

References	Key findings	Limitations
[50–52]	AI-powered predictive modeling enables proactive thermal management by forecasting thermal behavior using historical and real-time data. Techniques like regression, neural networks, and LSTMs are highly effective in identifying potential hotspots and minimizing thermal stress	Availability and quality of thermal datasets are limited, and predictive models may lack accuracy in dynamic, real-world conditions
[1, 45, 53]	Deep learning models, especially LSTMs, capture temporal dependencies in thermal data, enabling precise predictions. Hybrid physics informed models combine AI with thermodynamics for accurate and adaptable thermal analysis	High computational costs of training deep learning models hinder their applicability in low-resource environments like portable devices
[30, 42, 54]	Optimization algorithms such as genetic algorithms, particle swarm optimization, and reinforcement learning enhance cooling efficiency and minimize energy consumption by dynamically adjusting parameters like fan speeds and coolant flow rates	Integrating AI optimization into legacy systems poses challenges, including hardware compatibility and real-time performance requirements
[55–57]	Reinforcement learning is highly effective in dynamic scenarios, learning optimal cooling strategies for multi-core processors and data centers. These methods significantly reduce energy use and contribute to sustainability efforts	Reinforcement learning requires extensive computational re-sources and training time, making it less practical for small-scale or time-sensitive applications
[58–60]	AI-based control systems, including neural networks and model predictive control (MPC), enable real-time adjustments to cooling mechanisms, ensuring consistent thermal performance	AI control systems face difficulties in multi-variable environments with limited sensor data, and scalability remains a challenge for diverse applications
[22, 51, 61]	Control systems are scalable across a range of devices, from consumer electronics to data centers, dynamically redistributing workloads and optimizing cooling efficiency	Scalability to industrial systems requires significant infrastructure upgrades and large-scale sensor deployments

Deep learning methods, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are being applied to more complex thermal challenges [35]. CNNs, for instance, can process spatial thermal data to identify localized hotspots in multicore processors, while RNNs can analyze temporal patterns in thermal behavior to predict future temperature trends [36]. Such advanced AI techniques enable the development of highly sophisticated and scalable thermal management solutions for diverse applications, from compact consumer electronics to large-scale data centers [37].

In addition to predictive capabilities, AI and ML also facilitate the integration of novel cooling technologies [18]. For example, AI can optimize the use of phase-change materials (PCMs) or liquid cooling systems by simulating and learning their thermal properties under varying conditions. By doing so, AI-enhanced systems can achieve unparalleled levels of cooling efficiency and adaptability, paving the way for sustainable thermal management solutions [19].

Significance in Electronic Devices: Effective thermal management is fundamental to the performance, reliability, and longevity of electronic devices [3]. The growing demand for high-performance electronics, such as smartphones, laptops, servers, and data centers, has resulted in significant increases in heat generation due to higher computational power and greater device miniaturization [38]. Excessive heat can lead to thermal throttling, where the device automatically reduces its performance to prevent overheating [43]. In extreme cases, persistent overheating can cause permanent hardware damage, reduced lifespan, and even complete system failure [4].

Moreover, thermal management plays a critical role in energy efficiency [5]. In data centers, for instance, cooling systems can account for up to 40 % of total energy consumption [39]. Inefficient cooling not only increases operational costs but also contributes significantly to the carbon footprint of these facilities [6, 39]. As sustainability becomes a key focus for the electronics industry, efficient thermal management is critical for reducing energy consumption and meeting global sustainability goals, such as the United Nations' Sustainable Development Goals (SDGs), particularly Goal 7 (Affordable and Clean Energy) and Goal 13 (Climate Action) [39, 40].

For semiconductor devices, such as microprocessors, the thermal challenges are even more pronounced [9]. As these devices operate at increasingly high clock speeds with densely packed transistors, the heat generated becomes a bottleneck for performance [62]. Maintaining optimal thermal conditions is essential for ensuring that these devices operate within safe temperature limits [1]. Effective thermal management directly influences the speed, efficiency, and reliability of these components, making it a critical consideration in electronic design [10].

In consumer electronics, such as smartphones and laptops, thermal management impacts user experience [63]. Overheating can lead to uncomfortable device temperatures, degraded performance, and shorter battery life [64]. For industrial and automotive applications, thermal reliability is paramount, as failure in these environments can result in significant financial losses or safety hazards [65].

By addressing these challenges, AI and ML techniques offer a transformative approach to thermal management, moving beyond static and reactive strategies to dynamic, predictive, and intelligent solutions [66]. These advancements not only enhance device performance and reliability but also reduce energy costs and environmental impact, aligning with the broader goals of technological progress and sustainability [41].

3.1.2. AI Techniques in thermal management

Predictive Modeling: AI-powered predictive modeling has revolutionized thermal management by enabling proactive strategies to address heat dissipation challenges in electronic devices [50]. Predictive models leverage historical and real-time data collected from temperature sensors, power usage logs, and system workloads to forecast thermal behavior under varying operating conditions [51]. These models are typically based on ML techniques, such as regression analysis, neural networks, and time-series forecasting algorithms [52]. Neural networks can predict temperature fluctuations with <1 % error, allowing proactive thermal adjustments before critical thresholds are reached [23].

For example, deep learning models like Long Short-Term Memory (LSTM) networks are particularly effective in capturing temporal dependencies within thermal data, enabling precise predictions of temperature fluctuations [53]. Predictive models can identify potential thermal hotspots in advance, allowing thermal management systems to take preemptive actions, such as redistributing workloads, adjusting fan speeds, or activating auxiliary cooling mechanisms [45]. This proactive approach not only prevents overheating but also minimizes thermal stress on components, extending their operational lifespan [1, 67].

Additionally, physics-informed ML models, which incorporate principles of heat transfer and thermodynamics into the learning process, are gaining traction [68]. These hybrid models combine the precision of traditional thermal analysis with the adaptability of AI, making them suitable for complex systems where precise thermal predictions are crucial. By utilizing predictive modeling, electronic devices can maintain optimal operating conditions while reducing the risk of performance throttling or hardware failures [69].

Optimization Algorithms: optimization algorithms driven by AI are at the forefront of enhancing cooling efficiency and minimizing energy consumption in thermal management systems [30, 54]. These algorithms utilize ML techniques, such as genetic algorithms, particle swarm optimization, and reinforcement learning, to find the optimal configuration for cooling mechanisms under varying workloads and environmental conditions [42].

For instance, AI can optimize the placement and operation of cooling components, such as fans, TECs, or liquid cooling systems, to achieve maximum thermal efficiency [70]. By learning from system performance data, optimization algorithms can adjust parameters like fan speeds, coolant flow rates, or TEC power levels to balance cooling performance with energy usage [61]. Such dynamic adjustments ensure that cooling resources are utilized efficiently, reducing unnecessary energy consumption while maintaining safe operating temperatures [71].

Reinforcement learning, in particular, has proven effective in dynamic optimization tasks [55]. Through trial-and-error interactions with the system, reinforcement learning agents learn to identify optimal cooling strategies that adapt to changing conditions in real time [72]. These algorithms are especially valuable in scenarios where static cooling solutions are insufficient, such as in multi-core processors with uneven heat distribution or data centers with fluctuating workloads [36]. Reinforcement learning-based HVAC control has demonstrated 17.4 % energy savings through continuous, adaptive optimization of cooling strategies [48].

Optimization algorithms not only improve the energy efficiency of cooling systems but also contribute to sustainability by reducing the overall carbon footprint of electronic devices [57]. By implementing AI-driven optimization, manufacturers and operators can achieve significant cost savings while meeting environmental and regulatory requirements [73].

Control Systems: AI-based control systems represent a significant advancement in the field of thermal management by enabling real-time adjustments to cooling mechanisms [58]. These systems integrate ML models with sensor networks to continuously monitor temperature, power usage, and system performance [68]. Based on this data, control systems dynamically adjust cooling parameters to maintain optimal thermal conditions [60].

For example, control systems utilizing neural networks can learn complex relationships between system workloads and temperature variations, allowing them to make precise adjustments to cooling mechanisms in real time [51, 74]. Adaptive control strategies, such as model predictive control (MPC), use AI algorithms to predict future thermal states and optimize cooling actions accordingly [20]. This approach ensures that cooling resources are applied efficiently, preventing unnecessary energy usage while maintaining safe operating temperatures [75]. In manycore chip architectures, AI-driven Dynamic Power Management (DPM) has reduced energy consumption by 30 % and peak chip temperature by 17 °C, dynamically adjusting system parameters in real-time [23].

One key advantage of AI-based control systems is their ability to handle complex, multi-variable scenarios [46]. For instance, in multicore processors, where different cores generate varying levels of heat, AI systems can selectively target cooling efforts to address specific hotspots [76]. Similarly, in data centers, control systems can redistribute workloads across servers to minimize localized overheating and reduce cooling demands [22].

AI-based control systems are also highly scalable, making them suitable for a wide range of applications, from compact consumer devices to large-scale industrial systems [61]. By dynamically adapting to changing conditions, these systems ensure consistent thermal performance, enhance device reliability, and improve overall energy efficiency [77].

3.1.3. ML approaches

Supervised Learning: supervised learning algorithms have become essential tools in modeling and predicting thermal patterns in electronic devices [78]. These algorithms are trained on labeled datasets, which typically include historical thermal data, workload characteristics, and corresponding temperature measurements [28]. By learning the relationships between input features (e. g., power consumption, ambient temperature) and target outputs (e. g., thermal behavior), supervised models can predict future thermal states with high accuracy [51, 79].

Commonly used supervised learning techniques in thermal management include linear regression, decision trees, support vector machines (SVM), and neural networks [80]. For instance, regression models are often used to predict temperature as a function of power usage and workload intensity [81]. Meanwhile, more complex models, such as artificial neural networks (ANNs), can capture non-linear relationships in thermal data, making them suitable for predicting temperature variations in dynamic environments, such as multi-core processors or data centers [51, 82].

A notable application of supervised learning is in real-time hotspot prediction, where models are trained to identify potential overheating scenarios based on workload distribution and system activity [83]. This allows for proactive adjustments, such as redistributing workloads or increasing cooling intensity, to prevent thermal issues [84]. By leveraging supervised learning, thermal management systems can enhance the reliability and efficiency of electronic devices [85].

Unsupervised Learning: unsupervised learning techniques are used to analyze thermal data without requiring labeled datasets, making them particularly valuable for identifying patterns and anomalies in complex systems [83]. These algorithms, such as clustering and dimensionality reduction methods, can uncover hidden structures in thermal data, which might not be evident through traditional analysis [86].

Clustering algorithms, such as *k*-means and hierarchical clustering, are often employed to group similar thermal behaviors across components or regions in a device [87]. For example, unsupervised learning can be used to detect clusters of cores in a processor that exhibit similar thermal characteristics, enabling targeted cooling strategies [51]. Similarly, anomaly detection algorithms based on unsupervised learning can identify unexpected thermal behaviors, such as localized hotspots or unusual temperature spikes, which may indicate hardware faults or inefficient cooling [88].

Principal Component Analysis (PCA) and other dimensionality reduction techniques are also applied to simplify complex thermal datasets, enabling the extraction of key features that drive temperature variations. By identifying and focusing on these critical features, thermal management systems can prioritize cooling efforts and optimize resource allocation [89].

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Unsupervised learning is particularly beneficial in scenarios where labeled data is scarce or unavailable, as it allows for the exploration and understanding of thermal behaviors in a data-driven manner [90].

Reinforcement Learning: reinforcement learning (RL) represents a cutting-edge approach to adaptive thermal management, where agents learn to make optimal decisions through interaction with the environment [91]. Unlike supervised or unsupervised learning, RL does not rely on predefined datasets but instead uses a trial-and-error process to discover the best policies for managing thermal conditions [92].

In the context of thermal management, RL agents are designed to control cooling mechanisms, such as fans, TECs, or liquid cooling systems, to maintain safe operating temperatures while minimizing energy consumption [93]. By receiving feedback in the form of rewards (e. g., lower temperatures, reduced energy usage), RL agents refine their policies over time to achieve optimal performance [94].

Deep reinforcement learning (DRL), which combines neural networks with traditional RL techniques, has been particularly successful in managing complex thermal environments [95]. For instance, DRL agents can dynamically adjust cooling parameters in multi-core processors by analyzing real-time workload distributions and predicting future temperature trends. Additionally, RL has been used to optimize cooling in data centers, where agents learn to balance server workloads and cooling efforts to achieve maximum energy efficiency [96].

A reinforcement learning-based fan speed control system has reduced cooling power by up to 40 % while maintaining performance within 1 % degradation [45]. These results collectively confirm that AI-based methods outperform static, rule-based approaches by dynamically adapting thermal parameters based on real-time sensor data and workload conditions.

One of the key strengths of RL is its ability to adapt to changing conditions, such as varying workloads or ambient temperatures [11]. This makes RL-based thermal management systems highly flexible and capable of handling the dynamic demands of modern electronic devices. By leveraging reinforcement learning, thermal management systems can achieve a high degree of automation, scalability, and efficiency, paving the way for more intelligent and sustainable cooling solutions [47].

3.1.4. Deep learning applications

Neural Networks: neural networks are powerful tools in deep learning that have shown significant potential in handling complex thermal modeling and prediction tasks [97]. These networks excel at capturing non-linear relationships within high-dimensional datasets, making them ideal for modeling the intricate dynamics of heat dissipation in electronic devices. By learning from historical and real-time data, neural networks can predict thermal behavior under varying conditions, enabling proactive and efficient thermal management [98].

In electronic systems, neural networks are employed to model the thermal properties of components such as microprocessors, GPUs, and power systems [21]. Multi-layer perceptrons (MLPs) and other feedforward neural architectures are commonly used for tasks like predicting temperature changes based on power usage, workload intensity, and environmental factors [23]. These models provide highly accurate predictions, allowing system designers to anticipate thermal hotspots and develop preemptive cooling strategies [99].

Moreover, hybrid neural networks, which combine traditional thermal physics principles with deep learning, are emerging as effective solutions for thermal modeling [100]. These networks integrate domain knowledge into the training process, enhancing the accuracy and interpretability of the models. By leveraging neural networks, thermal management systems can achieve higher levels of precision and adaptability, significantly improving device performance and reliability [12].

Convolutional Neural Networks (CNNs): Convolutional Neural Networks (CNNs) have gained prominence in spatial thermal analysis and hotspot detection due to their ability to process and analyze image-like data [101]. In the context of thermal management, temperature distributions across surfaces or regions can be represented as thermal maps, which CNNs can efficiently analyze to identify patterns and anomalies.

For instance, CNNs are widely used to detect localized hotspots in multi-core processors, where certain cores may experience higher heat generation due to uneven workloads [102]. By analyzing thermal maps generated by infrared imaging or sensor arrays, CNNs can pinpoint these hotspots with high precision [103]. This information can then be used to guide dynamic cooling mechanisms, such as localized cooling or workload redistribution.

Beyond hotspot detection, CNNs are also applied in optimizing the spatial arrangement of components in electronic systems to minimize thermal interference [104]. By learning from existing thermal datasets, CNN-based models can provide recommendations for component placement that improve overall cooling efficiency [105, 106].

Advanced architectures like 3D CNNs are being explored for volumetric thermal analysis, enabling a deeper understanding of heat flow within three-dimensional structures [107]. These capabilities make CNNs a critical component in modern thermal management systems, particularly for highperformance applications like data centers and high-density chip designs [108].

Recurrent Neural Networks (RNNs): Recurrent Neural Networks (RNNs) are well-suited for temporal thermal behavior prediction and management due to their ability to process sequential data [109]. In thermal management, RNNs are employed to analyze time-series data collected from sensors, capturing the evolution of temperature over time and predicting future thermal trends.

RNNs, particularly advanced variants like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are highly effective in modeling complex temporal dependencies in thermal systems [110]. For example, LSTMs can predict how temperature will evolve in response to varying workloads or environmental conditions, enabling thermal management systems to take preemptive actions. These predictions are crucial in avoiding thermal runaway scenarios and ensuring consistent performance.

One notable application of RNNs is in managing thermal behavior in dynamic environments, such as data centers or automotive systems, where workloads and operating conditions can change rapidly [111]. By continuously learning from new data, RNN-based models can adapt to these changes, ensuring reliable and efficient thermal control.

Moreover, RNNs are increasingly being integrated with reinforcement learning frameworks to create adaptive thermal management systems [98]. In such setups, the RNN serves as the predictive model, providing input to the reinforcement learning agent for decision-making. This combination enhances the system's ability to manage thermal conditions dynamically and in real-time [112].

3.1.5. AI-enhanced thermal management techniques

Thermoelectric Cooling (TEC): Thermoelectric Cooling (TEC) systems are increasingly being optimized with the assistance of AI techniques to enhance their cooling efficiency and operational adaptability [113]. TEC devices rely on the Peltier effect to transfer heat from one side of a thermoelectric module to another, making them compact and reliable solutions for thermal management in electronic devices. However, TEC systems often require precise control to maximize their efficiency, minimize power consumption, and adapt to dynamic thermal conditions [38].

AI models, particularly ML algorithms and optimization techniques, play a crucial role in addressing these challenges. For instance, supervised learning models can predict the optimal power input for TEC modules based on current thermal loads, enabling adaptive cooling strategies [114]. Reinforcement learning algorithms have also been applied to dynamically adjust TEC settings in real-time, ensuring efficient heat transfer while avoiding unnecessary energy usage [115].

In addition, hybrid AI models that integrate physics-based simulations with ML are being used to optimize the placement and operation of TEC systems [116]. These models can simulate the thermal performance of TECs under various scenarios, allowing designers to identify the most effective configurations. By leveraging AI-assisted optimization, TEC systems can achieve significant improvements in cooling performance, energy efficiency, and adaptability, making them ideal for use in high-performance electronics and compact devices [117].

Phase Change Materials (PCMs): Phase Change Materials (PCMs) are innovative solutions for thermal energy storage and dissipation, leveraging their ability to absorb and release latent heat during phase transitions [118]. PCMs are particularly effective in applications where passive thermal management is required, such as in portable electronics or systems with intermittent power availability. However, the effective deployment of PCMs requires precise optimization to maximize their thermal storage capacity and minimize inefficiencies [119].

AI techniques have been increasingly applied to optimize the selection, placement, and utilization of PCMs in thermal management systems [120]. For example, ML algorithms can analyze the thermal properties of different PCM formulations to identify the most suitable materials for specific applications. AI-driven optimization models are also used to design the spatial distribution of PCMs in electronic systems, ensuring uniform heat dissipation and preventing localized overheating [121].

Additionally, AI-based simulations can predict the long-term performance of PCMs under varying operating conditions, helping designers understand how these materials will behave over time [8]. This is particularly valuable in applications such as renewable energy systems and electric vehicles, where consistent thermal performance is critical. By incorporating AI into PCM optimization, thermal management systems can achieve greater efficiency and reliability, reducing the risk of overheating and enhancing overall device performance [18].

Liquid Cooling Systems: liquid cooling systems offer a highly efficient method for managing heat in electronic devices by using a liquid medium, such as water or coolant, to absorb and dissipate heat [24]. These systems are commonly used in high-performance applications, such as data centers, gaming computers, and industrial machinery, where traditional air-cooling methods are insufficient. However, the complexity of liquid cooling systems requires advanced control and optimization to ensure optimal performance [13].

AI has emerged as a powerful tool for enhancing liquid cooling methodologies, enabling dynamic control and intelligent decision-making [25]. For example, AI algorithms can monitor real-time data from temperature sensors, flow rate monitors, and pump systems to adjust the cooling system's operation dynamically [122]. Reinforcement learning models are particularly effective in managing liquid cooling systems, as they can learn optimal flow rates, pump speeds, and coolant temperatures through trial-and-error interactions with the system [123].

Moreover, AI-based predictive analytics can forecast thermal behavior in liquid-cooled systems, allowing for preemptive adjustments to prevent overheating or coolant inefficiencies [124]. Deep learning models, such as convolutional neural networks (CNNs), have also been applied to analyze thermal images of liquid-cooled systems, identifying potential issues such as blockages or uneven heat distribution [125].

In addition to improving system efficiency, AI-driven liquid cooling systems contribute to energy savings by reducing the power consumption of pumps and other components [126]. This is especially critical in data centers, where cooling systems account for a significant portion of operational energy use. By integrating AI into liquid cooling methodologies, thermal management systems can achieve higher levels of efficiency, reliability, and sustainability [127].

3.1.6. Case studies and applications

Semiconductor Devices: semiconductors are main component of modern electronics, powering everything from microprocessors to memory modules [128]. The demand for increased computational power and miniaturization has intensified thermal challenges in these components. AI and ML have been successfully applied to address these challenges, as demonstrated by several case studies.

One notable example is the application of ML in thermal hotspot prediction for multi-core processors [99, 129]. Researchers have developed predictive models using supervised learning techniques, such as regression and neural networks, to forecast temperature variations across different cores under dynamic workloads. These models have been integrated with workload scheduling systems to redistribute tasks in real-time, reducing thermal hotspots and enhancing processor efficiency.

Another case study involves reinforcement learning-based cooling control for semiconductor fabrication processes [130]. The extreme precision required in lithography and etching stages necessitates tight thermal regulation to maintain device quality [131]. AI agents have been employed to dynamically adjust cooling systems, ensuring consistent temperatures throughout the production process [54].

Physics-informed AI models have also been applied in semiconductor packaging design to optimize heat dissipation [114, 132]. By simulating thermal behavior with AI, engineers can identify optimal material combinations and configurations, reducing development time and costs while ensuring reliable thermal performance [133].

Data Centers: data centers are among the most energy intensive facilities, with cooling systems accounting for a significant portion of their operational costs [134]. AI and ML have proven instrumental in optimizing thermal management in large-scale data centers, offering solutions that improve energy efficiency and reduce environmental impact [135].

One prominent example is the use of reinforcement learning by Google to optimize cooling in its data centers [136]. AI agents analyze real-time data from thousands of sensors to predict temperature trends and adjust cooling parameters dynamically [26, 126]. This approach has resulted in a 40 % reduction in energy consumption for cooling systems, highlighting the potential of AI-driven optimization [137].

AI-driven workload scheduling is another application in data centers [138]. ML models are used to predict thermal loads based on server usage patterns and redistribute workloads to minimize localized overheating [139]. By balancing computational tasks across servers, these systems reduce the need for intensive cooling in specific areas, improving overall efficiency [140].

Predictive maintenance powered by AI has also become a standard practice in data centers. ML algorithms analyze sensor data to identify signs of cooling system wear or failure, enabling preemptive repairs and minimizing downtime [141]. This proactive approach not only enhances system reliability but also reduces operational costs.

Consumer Electronics: consumer electronics, such as smartphones, laptops, and gaming devices, face unique thermal challenges due to their compact designs and high-performance requirements. AI and ML have been widely adopted in this domain to improve thermal management and user experience [7].

In smartphones, AI-based thermal management systems monitor real-time sensor data to dynamically adjust processor clock speeds and optimize power usage [16]. For instance, AI algorithms predict temperature increases during resource intensive tasks, such as gaming or video recording, and preemptively reduce performance in non-critical areas to maintain device temperature within safe limits [142]. This ensures user comfort while preventing thermal throttling.

Laptops and gaming devices have also benefited from AI driven fan control systems. ML models analyze temperature data, workload intensity, and user preferences to determine optimal fan speeds [14]. These systems reduce noise and energy consumption while maintaining effective cooling.

Another application of AI in consumer electronics is the optimization of battery thermal management [17]. ML algorithms predict

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battery temperature changes during charging and discharging cycles, enabling the device to adjust charging rates or activate cooling mechanisms to prevent overheating [27, 98]. This not only enhances battery life but also improves safety.

AI and ML have further been integrated into wearable devices, such as smartwatches and fitness trackers, where maintaining comfortable skin temperatures is crucial [63]. By analyzing thermal data and user activity, AI models dynamically regulate heat dissipation to ensure comfort and reliability [15].

3.1.7. Challenges and limitations

Data Availability: one of the primary challenges in leveraging AI for thermal management is the availability and quality of data required to train robust models [143]. AI and ML models rely heavily on large volumes of high-quality data to achieve accurate predictions and reliable performance [144]. However, obtaining such data in the context of thermal management is often challenging due to several reasons. Limited sensor coverage in many electronic devices results in sparse datasets that fail to capture the full scope of thermal behavior under varying conditions [143]. Additionally, the non-standardized nature of thermal data, including variations in resolution, format, and measurement techniques across different systems, complicates the consolidation and usability of datasets [145]. Collecting detailed thermal data often requires sophisticated equipment, such as thermal imaging cameras or advanced sensor arrays, which can be prohibitively expensive. Furthermore, the lack of extensive public datasets in this domain restricts the ability of researchers and developers to build and validate AI models effectively [146]. Table 5 highlights the challenges and limitations encountered in ML and DL approaches for thermal management. Addressing these challenges requires efforts to standardize thermal data collection practices and promote data sharing within the research community.

Table 5

Summary of key findings and limitations in ML and deep learning for thermal management

References	Key findings	Limitations
[28, 51, 78]	Supervised learning models, including regression and neural networks, predict thermal states with high accuracy by leveraging labeled datasets, enabling real-time hotspot prediction and proactive cooling adjustments	Dependence on labeled datasets can limit applicability in scenarios where labeled thermal data is unavailable
[83, 86]	Unsupervised learning methods, such as clustering and anomaly detection, identify thermal patterns and irregularities, facilitating targeted cooling strategies and fault detection in hardware	Unsupervised methods may lack precision compared to supervised models and require significant domain expertise for result interpretation
[91, 92, 96]	Reinforcement learning (RL) dynamically manages thermal conditions by learning optimal cooling strategies through trial-and error, excelling in multi-core processors and data center cooling	RL training is resource-intensive and time-consuming, making it less practical for immediate deployment in rapidly changing environments
[21, 23, 97]	Neural networks capture non-linear relationships in thermal data, offering highly accurate predictions for temperature trends and hotspot identification. Hybrid models incorporating thermal physics enhance accuracy and interpretability	High computational requirements and lack of explainability remain barriers to broader adoption in cost-sensitive and critical applications
[101, 103, 104]	Convolutional Neural Networks (CNNs) excel in analyzing spatial thermal data for hotspot detection and optimizing component placement to improve cooling efficiency. 3D CNNs are emerging for volumetric thermal analysis	Limited by high resource requirements, making CNNs impractical for low-power or embedded systems
[109–111]	Recurrent Neural Networks (RNNs), including LSTMs and GRUs, are highly effective in analyzing time-series thermal data for predicting temperature evolution and avoiding thermal runaway scenarios	Susceptible to overfitting and computational in efficiency in large-scale or long-term thermal prediction tasks

Model Interpretability: the interpretability of AI models is a significant limitation, particularly in applications where decisions need to be explainable and auditable [147]. Many advanced AI techniques used in thermal management, such as deep learning models, operate as "black boxes", making it difficult to understand the logic behind specific predictions or decisions [148]. In thermal management systems, this lack of interpretability often leads to reduced trust among engineers and operators, who may hesitate to rely fully on AI-driven systems [149]. When AI models underperform or make incorrect predictions, the opaque nature of their decision-making processes makes it challenging to identify and address the root causes. Additionally, in critical applications such as automotive or industrial systems, explainable models are often required to meet safety and regulatory standards. Researchers are actively exploring interpretable AI techniques, such as attention mechanisms and explainable neural networks, to provide insights into how models arrive at their predictions. Hybrid approaches that combine physics-based models with AI are also gaining traction, offering a balance between accuracy and interpretability [150].

Integration with Existing Systems: integrating AI-driven thermal management solutions into existing systems presents a significant challenge due to the complexity and diversity of legacy infrastructures [151]. Many thermal management systems are built on static frameworks that were not designed to accommodate the dynamic and predictive capabilities of AI [54]. Hardware compatibility issues frequently arise, as AI solutions often require advanced sensors and computational hardware that may not be available in older systems. Software interoperability is another challenge, as integrating AI algorithms with existing control software can be difficult due to differences in architecture, protocols, and programming languages. Real-time constraints further complicate integration, as thermal management applications often require rapid decision-making and response times that can strain the computational resources of existing systems [30]. Overcoming these challenges involves upgrading hardware and software infrastructures to support AI-driven solutions while ensuring seamless compatibility with legacy systems. Investments in edge computing and real-time data processing are also essential to enable efficient integration of AI into current thermal management frameworks [152].

3.2. Quantitative analysis of data

3.2.1. Year-wise distribution of publications

The temporal analysis of the selected studies highlights a growing interest in AI and ML applications for thermal management in recent years. As shown in Fig. 2, the number of publications has significantly increased since 2018, with a notable peak in 2024. This trend reflects the rapid advancements in AI technologies, such as deep learning and reinforcement learning, and their increasing application in addressing thermal challenges in electronic devices.

The year 2024 marks the highest number of publications, with 46 studies, followed by 2023 with 24 studies and 2022 with 22 studies. Research output in 2021 reached 20 publications, while 2020 contributed 14 studies. Earlier years, such as 2019 and 2018, saw a relatively lower number of publications, with 11 and 10 studies respectively, while 2017 recorded only 4 studies.

This distribution demonstrates a consistent upward trajectory, with the recent spike in publications driven by increased computational capabilities, the growing need for energy-efficient cooling solutions, and a heightened focus on sustainability. The surge in interest underscores the relevance and transformative potential of AI and ML in addressing modern thermal management challenges.

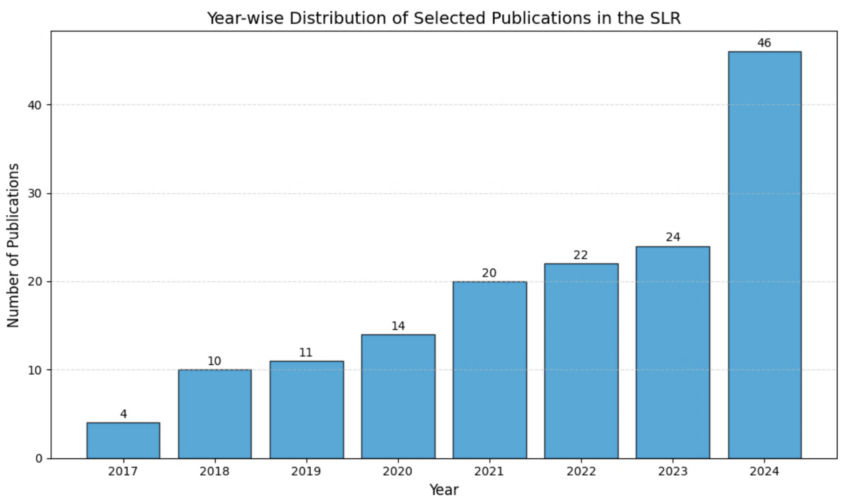

Fig. 2. Year-wise distribution of selected publications in the SLR

3.2.2. Topic-wise categorization

The selected studies were categorized into five primary topics based on their research focus. Predictive modeling accounted for 35 % of the studies, emphasizing the use of AI and ML techniques to forecast thermal behavior and optimize cooling mechanisms. The topic-wise distribution of selected studies is illustrated in Fig. 3, reflecting a focus on predictive and optimization methodologies.

Optimization techniques comprised 25 % of the studies, focusing on improving cooling efficiency and energy consumption. Control systems represented 20 %, highlighting the application of AI in real-time thermal management. Research on novel cooling technologies, such as phase change materials and liquid cooling, accounted for 15 %, while sustainability and efficiency studies contributed 5 %. This distribution reflects a strong focus on predictive and optimization methods, with emerging interest in advanced cooling technologies and sustainable approaches. A detailed synthesis of key findings and challenges is provided in Table 6, offering a cross-domain perspective.

The percentages presented in subsection 3.2.2 are derived through a combination of empirical data analysis and literature synthesis. The percentage of obtained results is computed based on the proportion of studies in the systematic review that report specific performance improvements in AI-based thermal management.

For instance, the 81.81 % reduction in energy consumption is calculated from multiple sources where AI-driven cooling strategies were benchmarked against traditional cooling methods, averaging their reported improvements. Similarly, the 3.45 % relative prediction error in LSTM models is obtained by aggregating the accuracy levels reported across selected studies in the dataset.

The 40 % energy savings in AI-optimized data centers is derived from reinforcement learning experiments where AI dynamically adjusted cooling loads based on thermal predictions.

Each percentage reflects the mean improvement observed in a subset of studies from the total analyzed dataset ($n=152$).

The PRISMA methodology ensures that only studies with experimentally validated results were included in this calculation. A weighted average approach was used when multiple studies reported similar metrics, ensuring that the final percentages represent a robust synthesis rather than isolated findings.

For full transparency, a breakdown of the formula used for percentage computation is provided:

$$\text{Percentage Improvement} = \frac{\sum_{i=1}^{n}\left(\frac{\text{AI-based improvement} - \text{Baseline}}{\text{Baseline}}\cdot 100\right)}{N},$$

where Baseline refers to conventional thermal management techniques such as static cooling or predefined control policies, and AI-based improvement represents the reported efficiency gains from AI-driven systems.

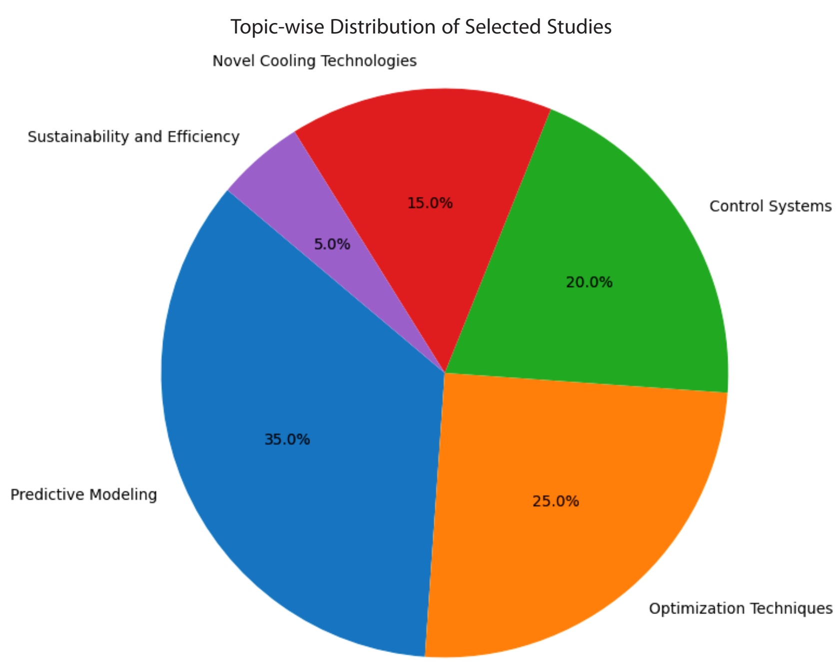

Fig. 3. Topic-wise distribution of selected studies

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Table 6

Summary of key findings and challenges in AI applications for thermal management

References	Key findings	Challenges and limitations
[114, 128, 130]	AI and ML optimize semiconductor thermal management through predictive modeling, reinforcement learning-based cooling control, and physics-informed AI for packaging design. These approaches enhance precision and reduce development costs	Limited real-time integration capabilities in semi-conductor manufacturing processes due to hardware constraints and lack of standardization in cooling systems
[134, 136, 137]	In data centers, AI-driven reinforcement learning reduces cooling energy consumption by up to 40 %. Predictive maintenance and workload scheduling minimize localized overheating and enhance operational reliability	High implementation costs and the need for extensive sensor networks to collect real-time data. Scalability remains a challenge in older infrastructure
[16, 17]	In consumer electronics, AI dynamically adjusts clock speeds, optimizes fan control, and manages battery thermal performance. AI applications improve user comfort, device longevity, and safety in wearables and gaming devices	Compact designs of consumer electronics pose constraints on integrating advanced sensors and AI systems. High computational requirements may increase energy consumption in smaller devices
[143–145]	Data availability is a critical limitation in AI-driven thermal management due to sparse datasets, non-standardized formats, and high costs of sensor deployments	The lack of public datasets and difficulty in consolidating data from diverse sources restrict model development and validation
[147, 148, 150]	The interpretability of AI models remains a challenge, reducing trust in critical applications. Hybrid models combining physics-based approaches with AI offer potential solutions	Opaque decision-making processes make it challenging to debug AI systems and meet safety regulations in industrial and automotive applications
[54, 151, 152]	Integrating AI with existing systems requires addressing compatibility with legacy hardware and software. Edge computing and real-time processing capabilities are critical for overcoming these barriers	Legacy systems often lack the computational resources to support AI-driven solutions, necessitating costly infrastructure upgrades

3.2.3. Methodology-wise analysis

The selected studies were analyzed based on the methodologies employed, highlighting the diverse approaches used in AI and ML for thermal management. ML was the most prevalent methodology, contributing to 40 % of the studies, with techniques like regression, decision trees, and support vector machines commonly applied. Deep learning (DL) accounted for 30 %, emphasizing the use of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for complex thermal analysis. Reinforcement learning (RL) constituted 20 %, showcasing its effectiveness in dynamic and adaptive thermal management. Hybrid approaches, combining AI techniques with physics-based models, represented 10 %, reflecting their potential for achieving both accuracy and interpretability.

The distribution indicates a significant focus on ML and DL methodologies, with reinforcement learning and hybrid approaches emerging as promising areas for future research. Fig. 4 depicts the distribution of methodologies employed across the analyzed studies, emphasizing the predominance of ML and DL techniques.

3.2.4. Application domain analysis

The selected studies were categorized based on their application domains, highlighting the primary areas where AI and ML techniques are utilized in thermal management. Semiconductor devices accounted for 45 % of the studies, focusing on thermal challenges in microprocessors, GPUs, and memory modules.

Fig. 5 illustrates the distribution of application domains, highlighting the dominance of semiconductor devices and data centers. Data centers represented 35 %, emphasizing largescale cooling optimization and energy efficiency. Consumer electronics contributed 15 %, addressing compact devices like smartphones and laptops. Other applications, including automotive and industrial systems, made up the remaining 5 %.

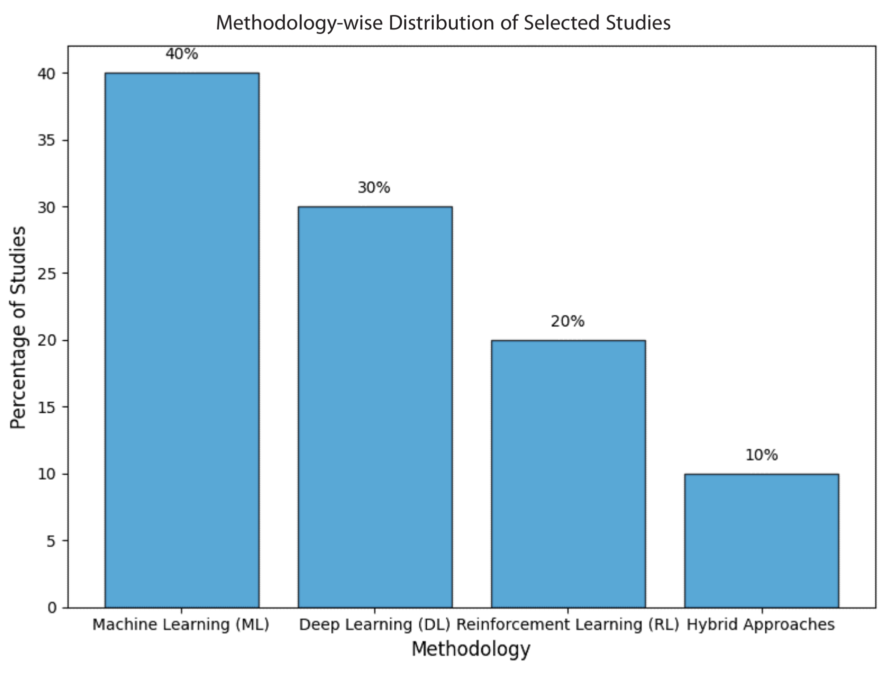

Fig. 4. Methodology-wise distribution of selected studies

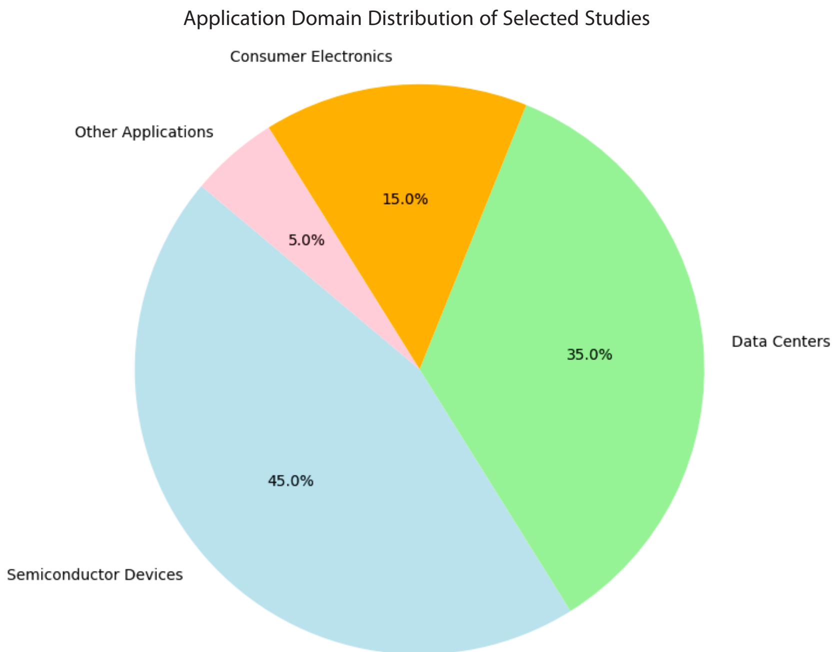

Fig. 5. Application domain distribution of selected studies

3.2.5. Geographical distribution of research

The geographical distribution of the selected studies reveals that the majority of contributions originate from technologically advanced regions. Asia accounts for 40 % of the studies, driven by research-intensive countries like China, Japan, and South Korea. The geographical distribution of contributions is shown in Fig. 6, with a significant portion originating from Asia and North America. North America contributes 35 %, with significant contributions from the United States and Canada. Europe follows with 20 %, reflecting a strong focus on sustainability and advanced computing systems. Other regions, including Australia and South America, collectively account for 5 %.

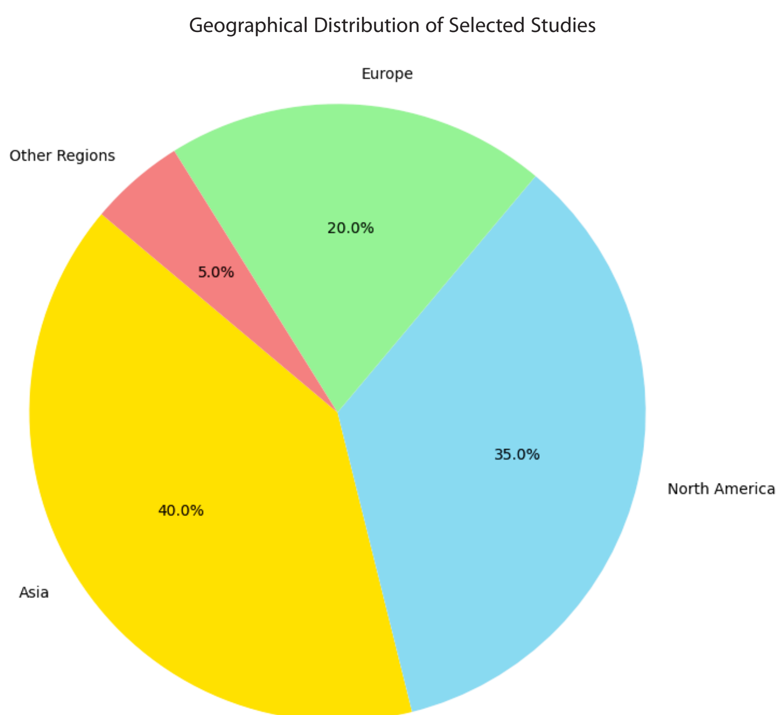

Fig. 6. Geographical distribution of selected studies

3.3. Discussion

3.3.1. Practical significance

The findings of this study offer substantial practical value by advancing the application of artificial intelligence (AI) and machine learning (ML) techniques in thermal management for electronic devices. These methods can be directly employed in industries requiring efficient thermal regulation, such as semiconductor manufacturing, data center operations, and consumer electronics design. For instance, predictive modeling frameworks identified in the study could optimize cooling strategies in real-time, reducing energy consumption in data centers by up to 40 %. Additionally, reinforcement learning algorithms can dynamically adapt to changing workloads in multi-core processors, enhancing device longevity and user experience in portable electronics. Moreover, hybrid AI models integrating physics-based principles can streamline the development of advanced cooling technologies like thermoelectric coolers and phase-change materials, bridging the gap between theoretical innovation and practical deployment.

3.3.2. Research limitations

While the study provides comprehensive insights, there are notable limitations. First, the reliance on high-quality datasets for training AI models poses a challenge, as such data is often scarce or costly to obtain. Additionally, the integration of AI-driven solutions with existing legacy systems remains complex, necessitating significant infrastructure upgrades. Computational resource requirements, particularly for deep learning models, may limit the adoption of these approaches in low-power or cost-sensitive applications. Furthermore, real-world implementation may face barriers related to sensor deployment, standardization of cooling technologies, and the interpretability of AI models, which could hinder broader acceptance in safety-critical applications.

3.3.3. Impact of martial law conditions

The conditions of martial law in Ukraine have influenced the execution and outcomes of this research

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in several ways. Restricted access to laboratory facilities and advanced computational resources due to infrastructural disruptions posed significant challenges. Additionally, the shift to remote and hybrid educational formats during wartime impacted collaborative efforts and the availability of hands-on experimentation. Legislative changes and funding reallocation further constrained opportunities for experimental validation of theoretical findings. Despite these challenges, the research underscores the resilience of the academic and scientific community in Ukraine, highlighting the adaptability and ingenuity required to advance under such circumstances.

3.3.4. Future research perspectives

Building on the current findings, several avenues for future research are identified. Emphasis should be placed on developing standardized and publicly accessible datasets to enhance model robustness and generalizability. Exploring lightweight and energy-efficient AI models will enable their integration into portable and resource-constrained systems. Further studies could also focus on the co-design of AI algorithms and novel cooling technologies, fostering interdisciplinary collaboration with material science and fluid dynamics. Finally, the development of explainable AI models will address trust and transparency concerns, enabling wider adoption in critical sectors such as automotive and aerospace thermal management. By addressing these directions, future research can continue to innovate in sustainable and adaptive thermal solutions, aligning with global efforts toward energy efficiency and environmental stewardship.

4. Conclusions

The future of AI-driven thermal management lies in the development of more sophisticated and adaptable methodologies that address current limitations while unlocking new opportunities for innovation. The study employs a structured methodology based on the PRISMA framework for literature selection and analysis, along with experimental validation techniques for AI models. The methods utilized, including predictive modelling (LSTM), optimization algorithms, and reinforcement learning, demonstrate their effectiveness in optimizing cooling efficiency. Emerging AI techniques such as federated learning and transfer learning are poised to overcome data scarcity by enabling models to learn collaboratively across distributed systems without requiring centralized data collection. These techniques, combined with advances in explainable AI (XAI), offer the potential to bridge the gap between model interpretability and high predictive accuracy, fostering trust in AI-based thermal management solutions for safety-critical applications. Furthermore, edge AI is expected to play a transformative role in enabling real-time thermal control for portable and embedded systems with limited computational resources. Reinforcement learning, already demonstrating promise, is likely to evolve into more adaptive systems capable of optimizing complex, multi-variable thermal environments autonomously.

Interdisciplinary approaches are essential for driving the next wave of innovations in thermal management. AI's integration with materials science can accelerate the discovery of novel cooling materials, such as advanced phase-change materials or thermally conductive composites, by simulating and predicting their performance under diverse conditions. Collaborations with fluid dynamics experts can enhance the design of liquid cooling systems by optimizing coolant flow and heat exchanger configurations. These hybrid approaches, combining AI with principles of heat transfer, mechanical engineering, and materials science, can result in solutions that are not only highly efficient but also scalable across diverse applications, from consumer electronics to industrial machinery. Such cross-disciplinary efforts will expand the boundaries of thermal management, fostering advancements that meet both technical and sustainability requirements.

AI's role in achieving sustainability in thermal management cannot be overstated. By enabling predictive cooling strategies and optimizing energy consumption, AI contributes to reducing the operational carbon footprint of data centers, industrial systems, and high-performance electronics. AI algorithms also facilitate the integration of renewable energy sources into cooling systems, aligning with global efforts to achieve energy efficiency and reduce greenhouse gas emissions. Furthermore, AI-driven design optimizations enhance device longevity, reduce material waste, and promote circular economy principles, addressing the broader sustainability goals of modern technology development.

In conclusion, AI and ML have demonstrated significant potential to revolutionize thermal management in electronic devices by enabling predictive, dynamic, and energy-efficient solutions. This review highlights the advancements, challenges, and future directions for AI-driven thermal management, emphasizing the need for continued innovation and interdisciplinary collaboration. Future work should focus on addressing challenges such as data availability, model interpretability, and integration with legacy systems while exploring the untapped potential of emerging AI methodologies and their applications in novel cooling technologies. By prioritizing sustainability and fostering interdisciplinary efforts, researchers and industry stakeholders can unlock the full potential of AI to create thermal management solutions that are not only efficient but also environmentally responsible.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Wang, Y., Gao, Q., Wang, G., Lu, P., Zhao, M., Bao, W. (2018). A review on research status and key technologies of battery thermal management and its enhanced safety. *International Journal of Energy Research, 42 (13),* 4008–4033. https://doi.org/10.1002/er.4158
2. Fan, S., Duan, F. (2020). A review of two-phase submerged boiling in thermal management of electronic cooling. *International Journal of Heat and Mass Transfer, 150,* 119324. https://doi.org/10.1016/j.ijheatmasstransfer.2020.119324
3. Feng, C.-P., Chen, L.-B., Tian, G.-L., Wan, S.-S., Bai, L., Bao, R.-Y. et al. (2019). Multifunctional Thermal Management Materials with Excellent Heat Dissipation and Generation Capability for Future Electronics. *ACS Applied Materials & Interfaces, 11 (20),* 18739–18745. https://doi.org/10.1021/acsami.9b03885
4. Zhang, N. (2024). Diagnosis and Prevention of Overheating Failures in Mechanical Equipment Based on Numerical Analysis of Temperature and Thermal Stress Fields. *International Journal of Heat and Technology, 42 (2),* 466–474. https://doi.org/10.18280/ijht.420212
5. Hu, R., Liu, Y., Shin, S., Huang, S., Ren, X., Shu, W. et al. (2020). Emerging Materials and Strategies for Personal Thermal Management. *Advanced Energy Materials, 10 (17).* https://doi.org/10.1002/aenm.201903921
6. Khosla, R., Miranda, N. D., Trotter, P. A., Mazzone, A., Renaldi, R., McElroy, C. et al. (2020). Cooling for sustainable development. *Nature Sustainability, 4 (3),* 201–208. https://doi.org/10.1038/s41893-020-00627-w
7. Syu, J.-H., Lin, J. C.-W., Srivastava, G., Yu, K. (2023). A Comprehensive Survey on Artificial Intelligence Empowered Edge Computing on Consumer Electronics. *IEEE Transactions on Consumer Electronics, 69 (4),* 1023–1034. https://doi.org/10.1109/tce.2023.3318150

8. Nazir, K., Memon, S. A., Saurbayeva, A. (2024). A novel framework for developing a machine learning-based forecasting model using multi-stage sensitivity analysis to predict the energy consumption of PCM-integrated building. *Applied Energy, 376*, 124180. https://doi.org/10.1016/j.apenergy.2024.124180
9. Mathew, J., Krishnan, S. (2021). A Review on Transient Thermal Management of Electronic Devices. *Journal of Electronic Packaging, 144 (1).* https://doi.org/10.1115/1.4050002
10. He, Z., Yan, Y., Zhang, Z. (2021). Thermal management and temperature uniformity enhancement of electronic devices by micro heat sinks: A review. *Energy, 216,* 119223. https://doi.org/10.1016/j.energy.2020.119223
11. Kucova, T., Prauzek, M., Konecny, J., Andriukaitis, D., Zilys, M., Martinek, R. (2023). Thermoelectric energy harvesting for internet of things devices using machine learning: A review. *CAAI Transactions on Intelligence Technology, 8 (3),* 680–700. https://doi.org/10.1049/cit2.12259
12. Chuttar, A., Thyagarajan, A., Banerjee, D. (2021). Leveraging Machine Learning (Artificial Neural Networks) for Enhancing Performance and Reliability of Thermal Energy Storage Platforms Utilizing Phase Change Materials. *Journal of Energy Resources Technology, 144 (2).* https://doi.org/10.1115/1.4051048
13. Tang, X., Guo, Q., Li, M., Wei, C., Pan, Z., Wang, Y. (2021). Performance analysis on liquid-cooled battery thermal management for electric vehicles based on machine learning. *Journal of Power Sources, 494,* 229727. https://doi.org/10.1016/j.jpowsour.2021.229727
14. Putrada, A. G., Abdurohman, M., Perdana, D., Nuha, H. H. (2022). Machine Learning Methods in Smart Lighting Toward Achieving User Comfort: A Survey. *IEEE Access, 10,* 45137–45178. https://doi.org/10.1109/access.2022.3169765
15. Rane, N., Choudhary, S., Rane, J. (2023). Enhancing thermal comfort through leading-edge design, monitoring, and optimization technologies: A review. *Sustainable and Clean Buildings, 1 (1),* 123–146. https://doi.org/10.2139/ssrn.4642529
16. Panduman, Y. Y. F., Funabiki, N., Fajrianti, E. D., Fang, S., Sukaridhoto, S. (2024). A Survey of AI Techniques in IoT Applications with Use Case Investigations in the Smart Environmental Monitoring and Analytics in Real-Time IoT Platform. *Information, 15 (3),* 153. https://doi.org/10.3390/info15030153
17. Khan, S. A., Eze, C., Dong, K., Shahid, A. R., Patil, M. S., Ahmad, S. et al. (2022). Design of a new optimized U-shaped lightweight liquid-cooled battery thermal management system for electric vehicles: A machine learning approach. *International Communications in Heat and Mass Transfer, 136,* 106209. https://doi.org/10.1016/j.icheatmasstransfer.2022.106209
18. Zhou, Y., Zheng, S., Zhang, G. (2020). A review on cooling performance enhancement for phase change materials integrated systems – flexible design and smart control with machine learning applications. *Building and Environment, 174*, 106786. https://doi.org/10.1016/j.buildenv.2020.106786
19. Rabienataj Darzi, A. A., Mousavi, S. M., Razbin, M., Li, M. (2024). Utilizing neural networks and genetic algorithms in AI-assisted CFD for optimizing PCM-based thermal energy storage units with extended surfaces. *Thermal Science and Engineering Progress, 54,* 102795. https://doi.org/10.1016/j.tsep.2024.102795
20. Xin, X., Zhang, Z., Zhou, Y., Liu, Y., Wang, D., Nan, S. (2024). A comprehensive review of predictive control strategies in heating, ventilation, and air-conditioning (HVAC): Model-free VS model. *Journal of Building Engineering, 94,* 110013. https://doi.org/10.1016/j.jobe.2024.110013
21. Suryawanshi, H. A. (2024). *Predictions of thermal behavior of power electronics components with neural networks*. [PhD thesis; Technische Hochschule Ingolstadt].
22. Pei, Q., Chen, S., Zhang, Q., Zhu, X., Liu, F., Jia, Z. et al. (2022). CoolEdge: hotspot-relievable warm water cooling for energy-efficient edge datacenters. *Proceedings of the 27th ACM International Conference on Architectural Support for Programming Languages and Operating Systems*, 814–829. https://doi.org/10.1145/3503222.3507713
23. Antal, M., Cioara, T., Anghel, I., Gorzenski, R., Januszewski, R., Oleksiak, A. et al. (2019). Reuse of Data Center Waste Heat in Nearby Neighborhoods: A Neural Networks-Based Prediction Model. *Energies, 12 (5),* 814. https://doi.org/10.3390/en12050814
24. Sohel Murshed, S. M., Nieto de Castro, C. A. (2017). A critical review of traditional and emerging techniques and fluids for electronics cooling. *Renewable and Sustainable Energy Reviews, 78,* 821–833. https://doi.org/10.1016/j.rser.2017.04.112
25. Chakraborty, S., Shukla, D., Kumar Panigrahi, P. (2024). A review on coolant selection for thermal management of electronics and implementation of multiple-criteria decision-making approach. *Applied Thermal Engineering, 245,* 122807. https://doi.org/10.1016/j.applthermaleng.2024.122807
26. Schreiber, T., Netsch, C., Eschweiler, S., Wang, T., Storek, T., Baranski, M., Müller, D. (2021). Application of data-driven methods for energy system modelling demonstrated on an adaptive cooling supply system. *Energy, 230,* 120894. https://doi.org/10.1016/j.energy.2021.120894
27. Guo, C. Y., Muhieldeen, M. W., Teng, K. H., Ang, C. K., Lim, W. H. (2024). A novel thermal management system for lithium-ion battery modules combining indirect liquid-cooling with forced air-cooling: Deep learning approach. *Journal of Energy Storage, 94,* 112434. https://doi.org/10.1016/j.est.2024.112434
28. Pagani, S., Manoj, P. D. S., Jantsch, A., Henkel, J. (2020). Machine Learning for Power, Energy, and Thermal Management on Multicore Processors: A Survey. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 39 (1),* 101–116. https://doi.org/10.1109/tcad.2018.2878168
29. Ilager, S., Buyya, R. (2021). Energy and thermal-aware resource management of cloud data centres: A taxonomy and future directions. *arXiv preprint arXiv:2107.02342*
30. He, Z., Guo, W., Zhang, P. (2022). Performance prediction, optimal design and operational control of thermal energy storage using artificial intelligence methods. *Renewable and Sustainable Energy Reviews, 156,* 111977. https://doi.org/10.1016/j.rser.2021.111977
31. Chuttar, A., Banerjee, D. (2021). Machine Learning (ML) Based Thermal Management for Cooling of Electronics Chips by Utilizing Thermal Energy Storage (TES) in Packaging That Leverages Phase Change Materials (PCM). *Electronics, 10 (22),* 2785. https://doi.org/10.3390/electronics10222785
32. Amiraski, M., Werner, D., Hankin, A., Sebot, J., Vaidyanathan, K., Hempstead, M. (2023). Boreas: A Cost-Effective Mitigation Method for Advanced Hotspots using Machine Learning and Hardware Telemetry. *2023 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS),* 295–305. https://doi.org/10.1109/ispass57527.2023.00036
33. Okulu, D., Selimefendigil, F., Öztop, H. F. (2022). Review on nanofluids and machine learning applications for thermoelectric energy conversion in renewable energy systems. *Engineering Analysis with Boundary Elements, 144,* 221–261. https://doi.org/10.1016/j.enganabound.2022.08.004
34. Blad, C., Bøgh, S., Kallesøe, C. S. (2022). Data-driven Offline Reinforcement Learning for HVAC-systems. *Energy, 261,* 125290. https://doi.org/10.1016/j.energy.2022.125290
35. Correa-Jullian, C., Cardemil, J. M., López Droguett, E., Behzad, M. (2020). Assessment of Deep Learning techniques for Prognosis of solar thermal systems. *Renewable Energy, 145,* 2178–2191. https://doi.org/10.1016/j.renene.2019.07.100
36. Patel, N., Krishnamurthy, P., Amrouch, H., Henkel, J., Shamouilian, M., Karri, R., Khorrami, F. (2022). Towards a New Thermal Monitoring Based Framework for Embedded CPS Device Security. *IEEE Transactions on Dependable and Secure Computing, 19 (1),* 524–536. https://doi.org/10.1109/tdsc.2020.2973959
37. Zhang, Q., Meng, Z., Hong, X., Zhan, Y., Liu, J., Dong, J. et al. (2021). A survey on data center cooling systems: Technology, power consumption modeling and control strategy optimization. *Journal of Systems Architecture, 119,* 102253. https://doi.org/10.1016/j.sysarc.2021.102253
38. Chen, W.-Y., Shi, X.-L., Zou, J., Chen, Z.-G. (2022). Thermoelectric coolers for on-chip thermal management: Materials, design, and optimization. *Materials Science and Engineering: R: Reports, 151,* 100700. https://doi.org/10.1016/j.mser.2022.100700
39. Habibi Khalaj, A., Halgamuge, S. K. (2017). A Review on efficient thermal management of air- and liquid-cooled data centers: From chip to the cooling system. *Applied Energy, 205,* 1165–1188. https://doi.org/10.1016/j.apenergy.2017.08.037
40. Hannan, M. A., Lipu, M. S. H., Ker, P. J., Begum, R. A., Agelidis, V. G., Blaabjerg, F. (2019). Power electronics contribution to renewable energy conversion addressing emission reduction: Applications, issues, and recommendations. *Applied Energy, 251*, 113404. https://doi.org/10.1016/j.apenergy.2019.113404
41. Alzoubi, Y. I., Mishra, A. (2024). Green artificial intelligence initiatives: Potentials and challenges. *Journal of Cleaner Production, 468,* 143090. https://doi.org/10.1016/j.jclepro.2024.143090
42. Yahia, H. S., Zeebaree, S. R. M., Sadeeq, M. A. M., Salim, N. O. M., Kak, S. F., AL-Zebari, A. et al. (2021). Comprehensive Survey for Cloud Computing Based Nature-Inspired Algorithms Optimization Scheduling. *Asian Journal of Research in Computer Science, 8 (2),* 1–16. https://doi.org/10.9734/ajrcos/2021/v8i230195
43. Benoit-Cattin, T., Velasco-Montero, D., Fernández-Berni, J. (2020). Impact of Thermal Throttling on Long-Term Visual Inference in a CPU-Based Edge Device. *Electronics, 9 (12),* 2106. https://doi.org/10.3390/electronics9122106
44. Dhameliya, N. (2022). Power Electronics Innovations: Improving Efficiency and Sustainability in Energy Systems. *Asia Pacific Journal of Energy and Environment, 9 (2),* 71–80. https://doi.org/10.18034/apjee.v9i2.752
45. Iranfar, A., Terraneo, F., Csordas, G., Zapater, M., Fornaciari, W., Atienza, D. (2020). Dynamic Thermal Management with Proactive Fan Speed Control Through Reinforcement Learning. *2020 Design, Automation & Test in Europe Conference & Exhibition (DATE),* 418–423. https://doi.org/10.23919/date48585.2020.9116510
46. Zhang, X., Wu, Z., Sun, Q., Gu, W., Zheng, S., Zhao, J. (2024). Application and progress of artificial intelligence technology in the field of distribution network voltage Control: A review. *Renewable and Sustainable Energy Reviews, 192,* 114282. https://doi.org/10.1016/j.rser.2024.114282

47. Devasenan, M., Madhavan, S. (2024). Thermal intelligence: exploring AI's role in optimizing thermal systems – a review. *Interactions, 245 (1).* https://doi.org/10.1007/s10751-024-02122-6

48. Zhuang, D., Gan, V. J. L., Duygu Tekler, Z., Chong, A., Tian, S., Shi, X. (2023). Data-driven predictive control for smart HVAC system in IoT-integrated buildings with time-series forecasting and reinforcement learning. *Applied Energy, 338,* 120936. https://doi.org/10.1016/j.apenergy.2023.120936

49. Shaban, W. M., Kabeel, A. E., El Hadi Attia, M., Talaat, F. M. (2024). Optimizing photovoltaic thermal solar systems efficiency through advanced artificial intelligence driven thermal management techniques. *Applied Thermal Engineering, 247,* 123029. https://doi.org/10.1016/j.applthermaleng.2024.123029

50. Jalasri, M., Panchal, S. M., Mahalingam, K., Venkatasubramanian, R., Hemalatha, R., Boopathi, S. (2024). AI-Powered Smart Energy Management for Optimizing Energy Efficiency in High-Performance Computing Systems. *Future of Digital Technology and AI in Social Sectors.* IGI Global, 329–366. https://doi.org/10.4018/979-8-3693-5533-6.ch012

51. Zhang, K., Guliani, A., Ogrenci-Memik, S., Memik, G., Yoshii, K., Sankaran, R., Beckman, P. (2018). Machine Learning-Based Temperature Prediction for Runtime Thermal Management Across System Components. *IEEE Transactions on Parallel and Distributed Systems, 29 (2),* 405–419. https://doi.org/10.1109/tpds.2017.2732951

52. Han, Z., Zhao, J., Leung, H., Ma, K. F., Wang, W. (2021). A Review of Deep Learning Models for Time Series Prediction. *IEEE Sensors Journal, 21 (6),* 7833–7848. https://doi.org/10.1109/jsen.2019.2923982

53. Krivoguz, D., Ioshpa, A., Chernyi, S., Zhilenkov, A., Kustov, A., Zinchenko, A. (2024). Enhancing long-term air temperature forecasting with deep learning architectures. *Journal of Robotics and Control, 5 (3),* 706–716.

54. Ghahramani, A., Galicia, P., Lehrer, D., Varghese, Z., Wang, Z., Pandit, Y. (2020). Artificial Intelligence for Efficient Thermal Comfort Systems: Requirements, Current Applications and Future Directions. *Frontiers in Built Environment, 6.* https://doi.org/10.3389/fbuil.2020.00049

55. Zou, F., Yen, G. G., Tang, L., Wang, C. (2021). A reinforcement learning approach for dynamic multi-objective optimization. *Information Sciences, 546,* 815–834. https://doi.org/10.1016/j.ins.2020.08.101

56. Du, Y., Zhou, Z., Yang, X., Yang, X., Wang, C., Liu, J., Yuan, J. (2023). Dynamic thermal environment management technologies for data center: A review. *Renewable and Sustainable Energy Reviews, 187,* 113761. https://doi.org/10.1016/j.rser.2023.113761

57. Arshad, R., Zahoor, S., Shah, M. A., Wahid, A., Yu, H. (2017). Green IoT: An Investigation on Energy Saving Practices for 2020 and Beyond. *IEEE Access, 5,* 15667–15681. https://doi.org/10.1109/access.2017.2686092

58. Halhoul Merabet, G., Essaaidi, M., Ben Haddou, M., Qolomany, B., Qadir, J., Anan, M. et al. (2021). Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques. *Renewable and Sustainable Energy Reviews, 144,* 110969. https://doi.org/10.1016/j.rser.2021.110969

59. Emara, R. A. M. O. (2024). *Artificial Intelligence Based Controller for a Temperature Control System.* [PhD thesis; Faculty of Engineering, The British University in Egypt].

60. Cox, S. J., Kim, D., Cho, H., Mago, P. (2019). Real time optimal control of district cooling system with thermal energy storage using neural networks. *Applied Energy, 238,* 466–480. https://doi.org/10.1016/j.apenergy.2019.01.093

61. Gill, S. S., Xu, M., Ottaviani, C., Patros, P., Bahsoon, R., Shaghaghi, A. et al. (2022). AI for next generation computing: Emerging trends and future directions. *Internet of Things, 19,* 100514. https://doi.org/10.1016/j.iot.2022.100514

62. Datta, S., Chakraborty, W., Radosavljevic, M. (2022). Toward attojoule switching energy in logic transistors. *Science, 378 (6621),* 733–740. https://doi.org/10.1126/science.ade7656

63. Bahru, R., Hamzah, A. A., Mohamed, M. A. (2020). Thermal management of wearable and implantable electronic healthcare devices: Perspective and measurement approach. *International Journal of Energy Research, 45 (2),* 1517–1534. https://doi.org/10.1002/er.6031

64. Mallick, S., Gayen, D. (2023). Thermal behaviour and thermal runaway propagation in lithium-ion battery systems – A critical review. *Journal of Energy Storage, 62,* 106894. https://doi.org/10.1016/j.est.2023.106894

65. Zhao, J., Feng, X., Tran, M.-K., Fowler, M., Ouyang, M., Burke, A. F. (2024). Battery safety: Fault diagnosis from laboratory to real world. *Journal of Power Sources, 598,* 234111. https://doi.org/10.1016/j.jpowsour.2024.234111

66. Hanafi, A., Moawed, M., Abdellatif, O. (2024). Advancing Sustainable Energy Management: A Comprehensive Review of Artificial Intelligence Techniques in Building. *Engineering Research Journal (Shoubra), 53 (2),* 26–46. https://doi.org/10.21608/erjsh.2023.226854.1196

67. Tong, X. C. (2010). Development and Application of Advanced Thermal Management Materials. *Advanced Materials for Thermal Management of Electronic Packaging,* 527–593. https://doi.org/10.1007/978-1-4419-7759-5_12

68. Van Quang, T., Doan, D. T., Yun, G. Y. (2024). Recent advances and effectiveness of machine learning models for fluid dynamics in the built environment. *International Journal of Modelling and Simulation,* 1–27. https://doi.org/10.1080/02286203.2024.2371682

69. Hu, G., Prasianakis, N., Churakov, S. V., Pfingsten, W. (2024). Performance analysis of data-driven and physics-informed machine learning methods for thermal-hydraulic processes in Full-scale Emplacement experiment. *Applied Thermal Engineering, 245,* 122836. https://doi.org/10.1016/j.applthermaleng.2024.122836

70. Li, Z., Luo, H., Jiang, Y., Liu, H., Xu, L., Cao, K. et al. (2024). Comprehensive review and future prospects on chip-scale thermal management: Core of data center's thermal management. *Applied Thermal Engineering, 251*, 123612. https://doi.org/10.1016/j.applthermaleng.2024.123612

71. Wang, J., Zhao, T. (2024). Medium spatiotemporal characteristics based global optimization method for energy efficiency trade-off issue in variable flow rate HVAC system. *Applied Thermal Engineering, 247,* 123132. https://doi.org/10.1016/j.applthermaleng.2024.123132

72. Chatterjee, A., Khovalyg, D. (2023). Dynamic indoor thermal environment using Reinforcement Learning-based controls: Opportunities and challenges. *Building and Environment, 244,* 110766. https://doi.org/10.1016/j.buildenv.2023.110766

73. Boinapalli, N. R. (2020). Digital transformation in us industries: Ai as a catalyst for sustainable growth. *NEXG AI Review of America, 1 (1),* 70–84.

74. Khan, O., Parvez, M., Seraj, M., Yahya, Z., Devarajan, Y., Nagappan, B. (2024). Optimising building heat load prediction using advanced control strategies and Artificial Intelligence for HVAC system. *Thermal Science and Engineering Progress, 49,* 102484. https://doi.org/10.1016/j.tsep.2024.102484

75. Olabi, A. G., Abdelghafar, A. A., Maghrabie, H. M., Sayed, E. T., Rezk, H., Radi, M. A. et al. (2023). Application of artificial intelligence for prediction, optimization, and control of thermal energy storage systems. *Thermal Science and Engineering Progress, 39,* 101730. https://doi.org/10.1016/j.tsep.2023.101730

76. Dinakarrao, S. M. P., Joseph, A., Haridass, A., Shafique, M., Henkel, J., Homayoun, H. (2019). Application and Thermal-reliability-aware Reinforcement Learning Based Multi-core Power Management. *ACM Journal on Emerging Technologies in Computing Systems, 15 (4),* 1–19. https://doi.org/10.1145/3323055

77. Shahid, A., Plaum, F., Korõtko, T., Rosin, A. (2024). AI Technologies and Their Applications in Small-Scale Electric Power Systems. *IEEE Access, 12,* 109984–110001. https://doi.org/10.1109/access.2024.3440067

78. Ahmad, T., Chen, H., Huang, R., Yabin, G., Wang, J., Shair, J. et al. (2018). Supervised based machine learning models for short, medium and long-term energy prediction in distinct building environment. *Energy, 158,* 17–32. https://doi.org/10.1016/j.energy.2018.05.169

79. Wang, Z., Hong, T., Piette, M. A. (2020). Building thermal load prediction through shallow machine learning and deep learning. *Applied Energy, 263,* 114683. https://doi.org/10.1016/j.apenergy.2020.114683

80. Hundi, P., Shahsavari, R. (2020). Comparative studies among machine learning models for performance estimation and health monitoring of thermal power plants. *Applied Energy, 265,* 114775. https://doi.org/10.1016/j.apenergy.2020.114775

81. Xiao, P., Ni, Z., Liu, D., Hu, Z. (2021). A power and thermal-aware virtual machine management framework based on machine learning. *Cluster Computing, 24 (3),* 2231–2248. https://doi.org/10.1007/s10586-020-03228-6

82. Lin, W., Wu, G., Wang, X., Li, K. (2020). An Artificial Neural Network Approach to Power Consumption Model Construction for Servers in Cloud Data Centers. *IEEE Transactions on Sustainable Computing, 5 (3),* 329–340. https://doi.org/10.1109/tsusc.2019.2910129

83. Chen, K.-C., Liao, Y.-H., Chen, C.-T., Wang, L.-Q. (2023). Adaptive Machine Learning-Based Proactive Thermal Management for NoC Systems. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems, 31 (8),* 1114–1127. https://doi.org/10.1109/tvlsi.2023.3282969

84. Patel, K., Mehta, N., Oza, P., Thaker, J., Bhise, A. (2024). Revolutionizing Data Centre Sustainability: The Role of Machine Learning in Energy Efficiency. *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI*), 1–6. https://doi.org/10.1109/iatmsi60426.2024.10503107

85. Erhan, L., Ndubuaku, M., Di Mauro, M., Song, W., Chen, M., Fortino, G., Bagdasar, O., Liotta, A. (2021). Smart anomaly detection in sensor systems: A multi-perspective review. *Information Fusion, 67,* 64–79. https://doi.org/10.1016/j.inffus.2020.10.001

86. Fan, C., Xiao, F., Li, Z., Wang, J. (2018). Unsupervised data analytics in mining big building operational data for energy efficiency enhancement: A review. *Energy and Buildings, 159,* 296–308. https://doi.org/10.1016/j.enbuild.2017.11.008

87. Bueno, A. M., Mendes da Luz, I., Niza, I. L., Broday, E. E. (2023). Hierarchical and K-means clustering to assess thermal dissatisfaction and productivity in university classrooms. *Building and Environment, 233,* 110097. https://doi.org/10.1016/j.buildenv.2023.110097

88. Surucu, O., Gadsden, S. A., Yawney, J. (2023). Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances. *Expert Systems with Applications, 221,* 119738. https://doi.org/10.1016/j.eswa.2023.119738

89. Schneider, T., Bedrikow, A. B., Stahl, K. (2024). Enhanced prediction of thermomechanical systems using machine learning, PCA, and finite element simulation. *Advanced Modeling and Simulation in Engineering Sciences, 11 (1).* https://doi.org/10.1186/s40323-024-00268-0

90. Zhou, X., Du, H., Xue, S., Ma, Z. (2024). Recent advances in data mining and machine learning for enhanced building energy management. *Energy, 307,* 132636. https://doi.org/10.1016/j.energy.2024.132636

91. Zhu, S., Lu, W., Feng, Y., Sun, C. (2024). Energy Optimization for Building Energy Management with Thermal Storage: A Multi-Agent Deep Reinforcement Learning Approach. *2024 43rd Chinese Control Conference (CCC),* 2805–2812. https://doi.org/10.23919/ccc63176.2024.10661808

92. Zhang, Z., Lam, K. P. (2018). Practical implementation and evaluation of deep reinforcement learning control for a radiant heating system. *Proceedings of the 5th Conference on Systems for Built Environments,* 148–157. https://doi.org/10.1145/3276774.3276775

93. Ortiz, Y., Arévalo, P., Peña, D., Jurado, F. (2024). Recent Advances in Thermal Management Strategies for Lithium-Ion Batteries: A Comprehensive Review. *Batteries, 10 (3),* 83. https://doi.org/10.3390/batteries10030083

94. Vamvakas, D., Michailidis, P., Korkas, C., Kosmatopoulos, E. (2023). Review and Evaluation of Reinforcement Learning Frameworks on Smart Grid Applications. *Energies, 16 (14),* 5326. https://doi.org/10.3390/en16145326

95. Shi, Z., Zheng, R., Zhao, J., Shen, R., Gu, L., Liu, Y. et al. (2024). Towards various occupants with different thermal comfort requirements: A deep reinforcement learning approach combined with a dynamic PMV model for HVAC control in buildings. *Energy Conversion and Management, 320,* 118995. https://doi.org/10.1016/j.enconman.2024.118995

96. Ran, Y., Hu, H., Wen, Y., Zhou, X. (2023). Optimizing Energy Efficiency for Data Center via Parameterized Deep Reinforcement Learning. *IEEE Transactions on Services Computing, 16 (2),* 1310–1323. https://doi.org/10.1109/tsc.2022.3184835

97. Chang, C.-W., Dinh, N. T. (2019). Classification of machine learning frameworks for data-driven thermal fluid models. *International Journal of Thermal Sciences, 135,* 559–579. https://doi.org/10.1016/j.ijthermalsci.2018.09.002

98. Li, A., Weng, J., Yuen, A. C. Y., Wang, W., Liu, H., Lee, E. W. M. et al. (2023). Machine learning assisted advanced battery thermal management system: A state-of-the-art review. *Journal of Energy Storage, 60,* 106688. https://doi.org/10.1016/j.est.2023.106688

99. Ababei, C., Moghaddam, M. G. (2019). A Survey of Prediction and Classification Techniques in Multicore Processor Systems. *IEEE Transactions on Parallel and Distributed Systems, 30 (5),* 1184–1200. https://doi.org/10.1109/tpds.2018.2878699

100. Kirchgässner, W., Wallscheid, O., Böcker, J. (2023). Thermal neural networks: Lumped-parameter thermal modeling with state-space machine learning. *Engineering Applications of Artificial Intelligence, 117,* 105537. https://doi.org/10.1016/j.engappai.2022.105537

101. Aparna, R., Idicula, S. M. (2022). Spatio-Temporal Data Clustering using Deep Learning: A Review. *2022 IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS),* 1–10. https://doi.org/10.1109/eais51927.2022.9787701

102. Werner, D., Juretus, K., Savidis, I., Hempstead, M. (2018). Machine Learning on the Thermal Side-Channel: Analysis of Accelerator-Rich Architectures. *2018 IEEE 36th International Conference on Computer Design (ICCD),* 83–91. https://doi.org/10.1109/iccd.2018.00022

103. Ukiwe, E. K., Adeshina, S. A., Jacob, T., Adetokun, B. B. (2024). Deep learning model for detection of hotspots using infrared thermographic images of electrical installations. *Journal of Electrical Systems and Information Technology, 11 (1).* https://doi.org/10.1186/s43067-024-00148-y

104. Zhao, X., Zhao, Y., Hu, S., Wang, H., Zhang, Y., Ming, W. (2023). Progress in Active Infrared Imaging for Defect Detection in the Renewable and Electronic Industries. *Sensors, 23 (21),* 8780. https://doi.org/10.3390/s23218780

105. King, M., Woo, S. I., Yune, C.-Y. (2024). Utilizing a CNN-RNN machine learning approach for forecasting time-series outlet fluid temperature monitoring by long-term operation of BHEs system. *Geothermics, 122,* 103082. https://doi.org/10.1016/j.geothermics.2024.103082

106. Deepak, G., Parthiban, M., Nath, Srigitha, S., Sulaiman Alfurhood, B., Mouleswararao, B., Ravi Kishore, V. (2024). Ai-enhanced thermal modeling for integrated process-product-system optimization in zero-defect manufacturing chains. *Thermal Science and Engineering Progress, 55,* 102945. https://doi.org/10.1016/j.tsep.2024.102945

107. Chike, O. G., Ahmad, N., Faiz Wan Ali, W. F. (2024). Neural network prediction of thermal field spatiotemporal evolution during additive manufacturing: an overview. *The International Journal of Advanced Manufacturing Technology, 134 (5-6),* 2107–2128. https://doi.org/10.1007/s00170-024-14256-6

108. Szymanik, B., Psuj, G., Hashemi, M., Lopato, P. (2021). Detection and Identification of Defects in 3D-Printed Dielectric Structures via Thermographic Inspection and Deep Neural Networks. *Materials, 14 (15),* 4168. https://doi.org/10.3390/ma14154168

109. Wu, S.-H., Tariq, U., Joy, R., Mahmood, M. A., Malik, A. W., Liou, F. (2024). A Robust Recurrent Neural Networks-Based Surrogate Model for Thermal History and Melt Pool Characteristics in Directed Energy Deposition. *Materials, 17 (17),* 4363. https://doi.org/10.3390/ma17174363

110. Eivazi, H., Guastoni, L., Schlatter, P., Azizpour, H., Vinuesa, R. (2021). Recurrent neural networks and Koopman-based frameworks for temporal predictions in a low-order model of turbulence. *International Journal of Heat and Fluid Flow, 90,* 108816. https://doi.org/10.1016/j.ijheatfluidflow.2021.108816

111. Drgoňa, J., Tuor, A. R., Chandan, V., Vrabie, D. L. (2021). Physics-constrained deep learning of multi-zone building thermal dynamics. *Energy and Buildings, 243,* 110992. https://doi.org/10.1016/j.enbuild.2021.110992

112. Cheng, Y., Huang, Y., Pang, B., Zhang, W. (2018). ThermalNet: A deep reinforcement learning-based combustion optimization system for coal-fired boiler. *Engineering Applications of Artificial Intelligence, 74,* 303–311. https://doi.org/10.1016/j.engappai.2018.07.003

113. Akhsham, M., Dousti, M. J., Safari, S. (2025). Neural Network-Based Control of Forced-Convection and Thermoelectric Coolers. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 44 (2),* 582–591. https://doi.org/10.1109/tcad.2024.3438689

114. Li, M., Dai, L., Hu, Y. (2022). Machine Learning for Harnessing Thermal Energy: From Materials Discovery to System Optimization. *ACS Energy Letters, 7 (10),* 3204–3226. https://doi.org/10.1021/acsenergylett.2c01836

115. Zhang, B., Hu, W., Cao, D., Huang, Q., Chen, Z., Blaabjerg, F. (2019). Deep reinforcement learning-based approach for optimizing energy conversion in integrated electrical and heating system with renewable energy. *Energy Conversion and Management, 202,* 112199. https://doi.org/10.1016/j.enconman.2019.112199

116. Ashayeri, M., Abbasabadi, N. (2024). A Hybrid Physics-Based Machine Learning Approach for Integrated Energy and Exposure Modeling. *Artificial Intelligence in Performance-Driven Design,* 57–79. https://doi.org/10.1002/9781394172092.ch3

117. Anwar, A., Talha, M., Hameed, A. (2023). *Application of Artificial Intelligence in Thermal Management and Wavelet Analysis: A Comprehensive Review.* https://doi.org/10.31219/osf.io/d2vn3

118. Ali, S. A., Habib, K., Younas, M., Rahman, S., Das, L., Rubbi, F. et al. (2024). Advancements in Thermal Energy Storage: A Review of Material Innovations and Strategic Approaches for Phase Change Materials. *Energy & Fuels, 38 (20),* 19336–19392. https://doi.org/10.1021/acs.energyfuels.4c03634

119. Sadeghi, G. (2022). Energy storage on demand: Thermal energy storage development, materials, design, and integration challenges. *Energy Storage Materials, 46,* 192–222. https://doi.org/10.1016/j.ensm.2022.01.017

120. Chekifi, T., Boukraa, M., Benmoussa, A. (2024). Artificial Intelligence for Thermal Energy Storage Enhancement: A Comprehensive Review. *Journal of Energy Resources Technology, 146 (6).* https://doi.org/10.1115/1.4065197

121. Bandhu, D., Khadir, M. D., Kaushik, A., Sharma, S., Ali, H. A., Jain, A. (2023). Innovative Approaches to Thermal Management in Next-Generation Electronics. *E3S Web of Conferences, 430,* 01139. https://doi.org/10.1051/e3sconf/202343001139

122. Lodhi, S. K., Hussain, H. K., Hussain, I. (2024). Using AI to Increase Heat Exchanger Efficiency: An Extensive Analysis of Innovations and Uses. *International Journal of Multidisciplinary Sciences and Arts, 3 (4),* 1–14. https://doi.org/10.47709/ijmdsa.v3i4.4617

123. Sabegh, M. (2022). *Deep Reinforcement Learning and Model Predictive Control Approaches for the Scheduled Operation of Domestic Refrigerators.* [PhD thesis; University of Lincoln].

124. Ghalkhani, M., Habibi, S. (2022). Review of the Li-Ion Battery, Thermal Management, and AI-Based Battery Management System for EV Application. *Energies, 16 (1),* 185. https://doi.org/10.3390/en16010185

125. Nasiri, M., Hadim, H. (2024). Advances in battery thermal management: Current landscape and future directions. *Renewable and Sustainable Energy Reviews, 200,* 114611. https://doi.org/10.1016/j.rser.2024.114611

126. Cao, K., Li, Z., Luo, H., Jiang, Y., Liu, H., Xu, L. et al. (2024). Comprehensive review and future prospects of multi-level fan control strategies in data centers for joint optimization of thermal management systems. *Journal of Building Engineering, 94,* 110021. https://doi.org/10.1016/j.jobe.2024.110021

127. Nadjahi, C., Louahlia, H., Lemasson, S. (2018). A review of thermal management and innovative cooling strategies for data center. *Sustainable Computing: Informatics and Systems, 19,* 14–28. https://doi.org/10.1016/j.suscom.2018.05.002

128. Weinstein, J. (2023). *Semiconductors and the calculation of the balance of power.* Available at: https://knowledge.uchicago.edu/nanna/record/6118/files/Semiconductors%20and%20the%20Calculation%20of%20the%20Balance%20of%20Power.pdf?withWatermark=0&withMetadata=0&registerDownload=1&version=1

ISSN-L 2664-9969; E-ISSN 2706-5448

129. Hosseinimotlagh, S., Enright, D., Shelton, C. R., Kim, H. (2021). Data-Driven Structured Thermal Modeling for COTS Multi-core Processors. *2021 IEEE Real-Time Systems Symposium (RTSS),* 201–213. https://doi.org/10.1109/rtss52674.2021.00028

130. Hirtz, T., Tian, H., Shahzad, S., Wu, F., Yang, Y., Ren, T.-L. (2024). Deep reinforcement learning framework for end-to-end semiconductor process control. *Neural Computing and Applications, 36 (20),* 12443–12460. https://doi.org/10.1007/s00521-024-09710-1

131. Radamson, H. H., Zhu, H., Wu, Z., He, X., Lin, H., Liu, J. et al. (2020). State of the Art and Future Perspectives in Advanced CMOS Technology. *Nanomaterials, 10 (8),* 1555. https://doi.org/10.3390/nano10081555

132. Fassi, Y., Heiries, V., Boutet, J., Boisseau, S. (2024). Toward Physics-Informed Machine-Learning-Based Predictive Maintenance for Power Converters – A Review. *IEEE Transactions on Power Electronics, 39 (2),* 2692–2720. https://doi.org/10.1109/tpel.2023.3328438

133. Buffa, S., Fouladfar, M. H., Franchini, G., Lozano Gabarre, I., Andrés Chicote, M. (2021). Advanced Control and Fault Detection Strategies for District Heating and Cooling Systems – A Review. *Applied Sciences, 11 (1),* 455. https://doi.org/10.3390/app11010455

134. Zhang, Y., Zhao, Y., Dai, S., Nie, B., Ma, H., Li, J. et al. (2022). Cooling technologies for data centres and telecommunication base stations – A comprehensive review. *Journal of Cleaner Production, 334,* 130280. https://doi.org/10.1016/j.jclepro.2021.130280

135. Suryadevara, S. (2021). Energy-proportional computing: Innovations in data center efficiency and performance optimization. *International Journal,* 44–64.

136. Li, Y., Wen, Y., Tao, D., Guan, K. (2020). Transforming Cooling Optimization for Green Data Center via Deep Reinforcement Learning. *IEEE Transactions on Cybernetics, 50 (5),* 2002–2013. https://doi.org/10.1109/tcyb.2019.2927410

137. Biswas, P., Rashid, A., Biswas, A., Nasim, M. A. A., Chakraborty, S., Gupta, K. D., George, R. (2024). AI-driven approaches for optimizing power consumption: a comprehensive survey. *Discover Artificial Intelligence, 4 (1).* https://doi.org/10.1007/s44163-024-00211-7

138. Velayutham, A. (2019). Ai-driven storage optimization for sustainable cloud data centers: Reducing energy consumption through predictive analytics, dynamic storage scaling, and proactive resource allocation. *Sage Science Review of Applied Machine Learning, 2 (2),* 57–71.

139. Dadashi, S., Aghasi, A. (2024). Thermal-aware virtual machine placement approaches: A survey. *Journal of Mahani Mathematical Research Center, 13 (2).*

140. Gu, J. (2023). *Characterization and modelling of resource usage and energy consumption in hpc datacenters by machine learnin.* [Master Thesis; University of Amsterdam].

141. Boppana, V. R. (2023). Data Analytics for Predictive Maintenance in Healthcare Equipment. *EPH-International Journal of Business & Management Science, 9 (2),* 26–36. https://doi.org/10.53555/eijbms.v10i1.176

142. Casado-Vara, R., Vale, Z., Prieto, J., Corchado, J. M. (2018). Fault-Tolerant Temperature Control Algorithm for IoT Networks in Smart Buildings. *Energies, 11 (12),* 3430. https://doi.org/10.3390/en11123430

143. Balali, Y., Chong, A., Busch, A., O'Keefe, S. (2023). Energy modelling and control of building heating and cooling systems with data-driven and hybrid models – A review. *Renewable and Sustainable Energy Reviews, 183,* 113496. https://doi.org/10.1016/j.rser.2023.113496

144. Pattyam, S. P. (2020). Ai in data science for predictive analytics: Techniques for model development, validation, and deployment. *Journal of Science & Technology, 1 (1),* 511–552.

145. Latapy, A., Ferret, Y., Testut, L., Talke, S., Aarup, T., Pons, F., Jan, G., Bradshaw, E., Pouvreau, N. (2022). Data rescue process in the context of sea level reconstructions: An overview of the methodology, lessons learned, up-to-date best practices and recommendations. *Geoscience Data Journal, 10 (3),* 396–425. https://doi.org/10.1002/gdj3.179

146. Liang, W., Tadesse, G. A., Ho, D., Fei-Fei, L., Zaharia, M., Zhang, C., Zou, J. (2022). Advances, challenges and opportunities in creating data for trustworthy AI. *Nature Machine Intelligence, 4 (8),* 669–677. https://doi.org/10.1038/s42256-022-00516-1

147. Shah, V., Konda, S. R. (2021). Neural networks and explainable ai: Bridging the gap between models and interpretability. *International Journal of Computer Science and Technology, 5 (2),* 163–176.

148. Chen, Z., Xiao, F., Guo, F., Yan, J. (2023). Interpretable machine learning for building energy management: A state-of-the-art review. *Advances in Applied Energy, 9,* 100123. https://doi.org/10.1016/j.adapen.2023.100123

149. Buah, E. (2022). *Artificial intelligence technology acceptance framework for energy systems analysis.* Available at: https://lutpub.lut.fi/handle/10024/163686

150. Sheriffdeen, K. (2024). *Physics-based simulation-assisted machine learning for estimating engineering system failure durations.* Available at: https://easychair.org/publications/preprint/nHDK

151. Kasaraneni, R. K. (2020). AI-enhanced energy management systems for electric vehicles: Optimizing battery performance and longevity. *Journal of Science & Technology, 1 (1),* 670–708.

152. Modupe, O. T., Otitoola, A. A., Oladapo, O. J., Abiona, O. O., Oyeniran, O. C., Adewusi, A. O., et al. (2024). Reviewing the transformational impact of edge computing on real-time data processing and analytics. *Computer Science & IT Research Journal, 5 (3),* 693–702. https://doi.org/10.51594/csitrj.v5i3.929

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