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Green AI: Strategies for Mitigating Carbon Footprints in Machine Learning Systems

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Abstract: ***The rapid growth of artificial intelligence (AI) and machine learning (ML) has raised critical concerns about their environmental impact, as training and deploying large-scale models demand vast computational resources and produce significant carbon emissions. Early research (2020–2022) diagnosed these challenges by quantifying AI's carbon footprint, exposing the lack of transparency in energy reporting, and proposing initial efficiency measures. More recent studies (2023–2025) have advanced mitigation strategies, including algorithmic innovations such as pruning and transfer learning, renewable-powered infrastructures, and lifecycle-aware deployment practices, while also embedding Green AI principles into sectors such as energy, healthcare, logistics, and corporate governance. Despite this progress, efforts remain fragmented, with persistent trade-offs between performance and sustainability, limited standardization, and uneven institutional adoption. This paper synthesizes developments across the last five years to provide a comprehensive understanding of Green AI. It identifies the main sources of AI's carbon footprint, evaluates mitigation strategies, and highlights sectoral applications, while critically examining the challenges and trade-offs that persist. Finally, it proposes a roadmap for embedding sustainability across the AI lifecycle—spanning algorithm design, infrastructure optimization, lifecycle management, and policy alignment. By reframing AI success metrics to balance performance with environmental responsibility, this study positions Green AI not only as a technical adjustment but as a foundational principle for sustainable digital transformation.***

Keywords: Green AI, Sustainable machine learning, Carbon footprint reduction, Energy- efficient algorithms, AI governance

1. Introduction

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has witnessed exponential growth in recent years, driving advancements across industries ranging from healthcare to finance and energy systems. This rapid progress, however, has come at a significant environmental cost. Training state-of-the-art ML models, especially large-scale deep neural networks and foundation models, requires massive computational power and energy resources, leading to substantial carbon emissions (Zhang et al., 2025). As AI applications continue to scale, the environmental footprint of these systems has become a critical concern, prompting the emergence of "Green AI," an approach that emphasizes efficiency, sustainability, and responsible development (Alshamrani, 2025).

The carbon footprint of ML arises primarily from the energy-intensive processes of model training, inference, and deployment. A single large natural language processing (NLP) model can emit as much carbon dioxide as several cars over their entire lifetimes (Schodl et al., 2025). This environmental burden is exacerbated by the increasing demand for foundation models, such as large language models (LLMs), that require billions of parameters and extensive training datasets. While AI researchers have historically focused on performance improvements measured by accuracy or predictive power, the sustainability dimension of AI has often been overlooked (Li et al., 2025). Addressing this imbalance requires strategies that integrate ecological responsibility into the core design and operationalization of machine learning systems.

The call for sustainable AI practices has led to a new wave of research advocating for energy efficiency and low-carbon innovation. For instance, Nasar and Al-Batahari (2025) propose a green computing framework that quantifies the carbon costs of AI models and develops strategies for mitigation. Similarly, Masciari and Napolitano (2025) highlight hybrid estimation techniques, such as Green Algorithms, to more accurately measure the environmental impact of AI workloads. These studies underline a growing consensus: for AI to serve society responsibly, its development must align with global climate goals and sustainability commitments.

Several strategies have emerged to address the carbon footprint challenge in AI. These include algorithmic innovations that reduce computational complexity, dataset curation methods that minimize redundant training, and hardware improvements that lower energy consumption (Alshamrani, 2025). Beyond the laboratory, AI-driven optimization of industrial processes and energy systems can contribute to decarbonization at scale. For example, Kumar, Shekhar, and Tewary (2025) show how machine learning improves climate data management, reducing inefficiencies in industrial emissions monitoring. Meanwhile, Pal (2025) demonstrates the role of AI in supporting resilient and green energy infrastructure, highlighting how technological innovation can support broader decarbonization agendas.

At the same time, the field of Green AI is not without its challenges. One major issue is the lack of standardized reporting mechanisms for carbon emissions associated with AI training and inference (Borraccia et al., 2025). Without transparent accounting, it becomes difficult to compare models and establish benchmarks for sustainable practices.

Another barrier is the performance trade-off: researchers are often reluctant to adopt low-carbon strategies if they perceive them as compromising accuracy or speed (Zhang et al., 2025). Overcoming this tension requires rethinking evaluation metrics in AI research to balance accuracy with environmental efficiency, as proposed by Schodl et al. (2025), who advocate for experimental design frameworks that consider energy usage alongside predictive power.

The urgency of adopting Green AI practices is underscored by the broader context of global climate change. With AI increasingly embedded in critical infrastructures, such as smart grids, transportation, and healthcare systems, its environmental costs are no longer an abstract concern but a pressing policy issue (Saini et al., 2025). Integrating environmental, social, and governance (ESG) principles into AI deployment offers a pathway to sustainable digital transformation (Soomro et al., 2026). Moreover, sector-specific applications, such as resource optimization in data centers (RV, 2025) and efficient fine-tuning of LLMs (Alshamrani, 2025), demonstrate that Green AI is both technically feasible and economically beneficial.

Despite significant progress, critical research gaps remain. While current studies provide frameworks and metrics for carbon accounting, few offer holistic strategies that integrate algorithmic design, hardware efficiency, and lifecycle analysis of AI systems (Bhagat et al., 2025). Similarly, while policy literature emphasizes AI's potential role in sustainable development, there is a lack of interdisciplinary work bridging technical research with regulatory frameworks. This fragmentation limits the ability of stakeholders to develop comprehensive approaches to AI sustainability.

This paper addresses these gaps by presenting a systematic study of strategies for mitigating the carbon footprints of machine learning systems. It synthesizes recent advances in sustainable AI design, evaluates emerging methodologies for carbon tracking, and explores innovative practices that align AI with broader climate objectives. Specifically, this study seeks to: (1) critically assess the state of the art in Green AI; (2) highlight effective strategies for reducing carbon emissions across the ML lifecycle; and (3) identify opportunities for future research and policy interventions. In doing so, the paper contributes to the growing discourse on sustainable AI by offering a roadmap for integrating environmental responsibility into the heart of machine learning innovation.

2. Research Framework

2.1 Research Questions

The environmental implications of artificial intelligence (AI) and machine learning (ML) have become a growing concern, as training and deploying large-scale models demand vast computational resources and generate significant carbon emissions. While early research (2020–2022) highlighted the scale of this problem and proposed preliminary solutions, more recent studies (2023–2025) have broadened the scope by embedding Green AI principles into sectoral applications and governance frameworks. Building on this evolution, the present study addresses the following research questions:

RQ 1: How has research from 2020 to 2025 evolved in identifying and measuring the carbon footprint of machine learning systems across their lifecycle?

RQ 2: Which mitigation strategies—spanning algorithms, infrastructures, and lifecycle practices—have proven effective, and how have these approaches advanced over time?

RQ 3: In what ways are Green AI principles being applied across sectors such as energy, healthcare, logistics, and governance, and what gaps remain in embedding them within global sustainability frameworks?

These questions are designed to capture both the diagnosis of AI's carbon footprint and the progression of solutions, while also probing the degree to which Green AI has been mainstreamed into broader socio-technical systems.

2.2 Research Objectives

Aligned with the above questions, this study pursues four interrelated objectives:

1) To identify and critically analyze the evolution of research on carbon emissions across the ML lifecycle, paying particular attention to emerging methods for systematic measurement and transparent reporting.
2) To examine and compare mitigation strategies at the algorithmic, infrastructural, and lifecycle levels, highlighting their effectiveness and tracing how these approaches have advanced between early and recent scholarship.
3) To explore sector-specific applications of Green AI in energy, healthcare, logistics, and governance, while identifying gaps in cross-sectoral integration and scalability.
4) To synthesize these insights into a comprehensive roadmap for embedding sustainability across the AI lifecycle, bridging technical innovation, infrastructure optimization, lifecycle management, and policy alignment.

By pursuing these objectives, the study contributes both a conceptual synthesis of the field's development and a practical framework for advancing Green AI as a cornerstone of sustainable digital transformation.

2.3 Research Methodology

This study adopts a systematic literature review and integrative synthesis approach, drawing on peer-reviewed scholarship and authoritative reports published between 2020 and 2025. Sources were collected from leading databases- including IEEE Xplore, ScienceDirect, SpringerLink, and Frontiers- as well as preprints from arXiv and selected industry white papers. Keyword-based searches were conducted using terms such as "Green AI," "sustainable machine learning," "carbon footprint AI," "energy-efficient algorithms," and "AI sustainability."

Inclusion criteria prioritized works that demonstrated methodological rigor, direct relevance to AI sustainability, and contributions to carbon accounting, mitigation strategies,

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or sectoral applications. Exclusion criteria eliminated papers that were purely speculative, lacked empirical grounding, or addressed AI ethics without a sustainability component.

The selected studies were organized thematically into four categories:
1) Conceptual frameworks and definitions of Green AI.
2) Strategies for mitigation, including algorithmic, infrastructural, and lifecycle-oriented approaches.
3) Sectoral applications, spanning energy, healthcare, logistics, and ESG-driven governance.
4) Challenges and future directions, including performance–sustainability trade-offs, reporting gaps, and institutional barriers.

A comparative analysis was then conducted to trace the evolution of the field, distinguishing early research (2020–2022), which focused on diagnosing problems and proposing initial solutions, from more recent studies (2023–2025), which emphasized applied strategies, policy integration, and cross-sectoral deployment. This evolutionary lens allows the study not only to catalog existing contributions but also to highlight convergences, divergences, and persistent gaps.

Finally, the findings were synthesized into a conceptual roadmap that integrates insights from across the literature. This roadmap serves both as a summary of current best practices and as a guide for embedding sustainability into the design, deployment, and governance of AI systems.

3. Literature Review

3.1. Background and Conceptual Framework

3.1.1 Defining Green AI

The concept of Green AI emerged as scholars began questioning the sustainability of performance-driven artificial intelligence. Schwartz et al. (2020) introduced the distinction between Red AI, which prioritizes accuracy at any computational cost, and Green AI, which emphasizes efficiency, transparency, and ecological responsibility. Wu, Raghavendra, and Gupta (2022) expanded this critique by documenting the environmental implications of large- scale AI models, noting the exponential rise in training costs and energy demands. Pedrycz (2022) framed Green AI as an extension of responsible AI, calling for ecological awareness to be embedded in research agendas.

Building on these foundations, recent studies have reframed Green AI as a holistic framework rather than a niche concern. Alonso-Betanzos (2025) emphasized rethinking efficiency as a core design principle in ML architectures, while Vrana and Mondal (2025) positioned Green AI as central to global climate mitigation strategies. Similarly, Nasar and Al-Batahari (2025) proposed a comprehensive sustainability framework for AI, integrating efficiency with accountability and policy alignment. Together, this progression illustrates a shift from conceptual awareness in early works to integrated frameworks in contemporary research.

3.1.2 Sources of Carbon Footprint in AI/ML

Early studies focused on identifying the most carbon-intensive stages of the machine learning lifecycle. Strubell, Ganesh, and McCallum (2020) showed that training a single NLP model could emit carbon equivalent to multiple lifetimes of an average car. Pimentel et al. (2021) highlighted the contribution of cloud data centers, many of which still depend on fossil fuels. Wu et al. (2022) further emphasized lifecycle assessments, showing that emissions extend beyond training to deployment and infrastructure.

Recent work has expanded these insights into sector-specific contexts. Schodl, Lesota, and Tommasel (2025) quantified emissions from recommender systems, while Patel, Dua, and David (2025) explored cloud workload optimization for sustainability. Ibeama et al. (2025) linked Green AI practices to corporate sustainability in digital advertising, broadening the conversation from isolated models to industry-wide systems. This shift marks a transition from training-centered analysis to lifecycle and application-specific assessments.

3.1.3 Measuring AI's Environmental Impact

Efforts to measure AI's carbon footprint began with the Green Algorithms framework (Lacoste et al., 2019), which standardized energy and emissions reporting. Henderson et al. (2020) criticized the lack of transparency in ML publications, calling for mandatory compute and energy disclosures. Wu et al. (2022) argued for lifecycle-based evaluations to capture emissions from training, inference, and hardware disposal.

Recent advances move beyond reporting toward policy integration. Borraccia, Masciari, and Napolitano (2025) developed hybrid estimation techniques to improve accuracy in carbon accounting, while Islam, Badhan, and Islam (2025) proposed embedding AI-based carbon metrics within national carbon pricing systems. These innovations demonstrate a shift from reporting frameworks to institutionalized accounting mechanisms that align with climate policies.

3.2 Strategies for Mitigating Carbon Footprints

3.2.1 Algorithmic Innovations

Early mitigation strategies emphasized algorithmic efficiency. Dodge et al. (2020) demonstrated the benefits of training optimization methods such as early stopping, while Bommasani et al. (2021) showed how transfer learning reduces redundant computation. Patterson et al. (2021) highlighted the role of algorithm–hardware co-design in improving efficiency.

Recent studies expand these techniques into applied contexts. Stephen, Udo, and Asuquo (2025) applied Green AI strategies in healthcare models, while Raghuvanshi et al. (2025) explored AI-driven policies for hydrogen energy transitions. Alshamrani (2025) introduced linguistically-informed dataset curation to make large language model fine-tuning more efficient. These works signal a move from generic efficiency improvements to domain-specific algorithmic applications.

3.2.2 Dataset Curation and Training Optimization

Strubell et al. (2020) advocated for dataset curation to avoid brute-force scaling, while Dodge et al. (2020) emphasized optimization of training order and hyperparameters.

Bommasani et al. (2021) demonstrated the potential of few-shot learning in reducing training costs.

More recent work strengthens this direction. Alshamrani (2025) demonstrated that curated, high-quality datasets reduce carbon costs in LLM training. Nasar and Al-Batahari (2025) introduced frameworks that embed carbon-awareness into training pipelines. These contributions advance dataset optimization from academic proposals to practical implementation frameworks.

3.2.3 Hardware and Infrastructure Efficiency

During 2020–2022, hardware efficiency was highlighted by Patterson et al. (2021) and Jouppi et al. (2021), who demonstrated that specialized TPUs achieved significant energy savings compared to GPUs. Data center innovations such as renewable energy integration were also explored (Pimentel et al., 2021).

By 2023–2025, the focus shifted to systemic infrastructure sustainability. Ahmed et al. (2025) surveyed neuromorphic computing as a low-energy alternative, and Tripathi, Rambabu, and Krishna (2025) studied AI-optimized green data centers with dynamic cooling strategies. The emphasis thus evolved from chip-level efficiency to renewable-powered infrastructures.

3.2.4 Lifecycle and Deployment Practices

Henderson et al. (2020) emphasized deployment trade-offs, noting differences in emissions between edge and cloud inference. Strubell et al. (2020) advocated for reusing pretrained models as a way to avoid unnecessary retraining.

Contemporary studies have expanded lifecycle thinking. Alonso-Betanzos (2025) argued for lifecycle-based sustainability assessments, and Oyenuga et al. (2025) integrated AI into global decarbonization strategies, showing that lifecycle considerations must include policy and institutional contexts. This evolution highlights a shift from reuse and deployment trade-offs to holistic lifecycle frameworks.

3.3 Sector-Specific Applications of Green AI

3.3.1 AI in Energy Systems

Early research explored AI's role in optimizing energy efficiency and renewable integration. For instance, Pimentel et al. (2021) examined the role of cloud data centers in energy transitions, highlighting both their carbon intensity and potential for sustainability when powered by renewables. Wu et al. (2022) stressed that lifecycle assessments should include energy infrastructure when evaluating AI's environmental footprint.

Recent studies expand these insights into practical deployments. Pal (2025) demonstrated AI- driven smart grids that support renewable integration and resilience in energy infrastructure, while Raghuvanshi et al. (2025) highlighted AI-enabled policies for advancing hydrogen energy transitions. Tripathi, Rambabu, and Krishna (2025) further showed how AI-optimized cooling strategies in data centers reduce energy demand. The shift is clear: from diagnosing AI's role in energy systems to using AI as a tool for decarbonization.

3.3.2 Climate and Environmental Monitoring

Between 2020 and 2022, researchers began applying AI to environmental data analytics. Strubell et al. (2020) and Henderson et al. (2020) called for carbon tracking and transparency in AI publications, while Dodge et al. (2020) demonstrated how optimized ML training could reduce unnecessary emissions from climate modeling tasks.

By 2023–2025, applications became more policy-oriented and integrated. Kumar, Shekhar, and Tewary (2025) used AI for climate data management, improving industrial emissions monitoring, while Islam, Badhan, and Islam (2025) integrated AI into carbon pricing systems. Ibeama et al. (2025) connected Green AI with corporate sustainability practices in digital advertising, underscoring that AI-based environmental monitoring is now extending to corporate governance and reporting.

3.3.3 Healthcare and Public Health

Early applications of Green AI in healthcare focused primarily on efficiency in computational medicine. Dodge et al. (2020) showed how early stopping methods could reduce training costs for predictive models without sacrificing accuracy.

More recent works highlight domain-specific implementations. Stephen, Udo, and Asuquo (2025) demonstrated energy-efficient obesity prediction models that reduce emissions while maintaining accuracy. Karamagi, Okuonzi, and Mwanje (2025) examined AI-driven systems for equitable global health delivery, emphasizing the sustainability dimension of healthcare infrastructures. This shift reflects movement from general model efficiency to applied, sustainability-driven healthcare solutions.

3.3.4 Business, Governance, and ESG Integration

Between 2020 and 2022, sustainability in AI governance was largely discussed in terms of what should be done. Henderson et al. (2020) called for mandatory carbon reporting, and Schwartz et al. (2020) proposed efficiency as a new metric of AI progress.

By 2023–2025, Green AI became more embedded in corporate governance frameworks. Soomro, Rafi, and Abbasi (2026) illustrated how ESG frameworks integrate Green AI into sustainable business strategies. Patel, Dua, and David (2025) proposed sustainable cloud workload optimization for enterprise adoption, while Ibeama et al. (2025) showed how adopting Green AI in digital advertising aligns with corporate carbon reduction targets. Here, the discourse shifted from advocacy for sustainable governance to operationalization within ESG systems.

3.3.5 Logistics and Supply Chains

Applications in logistics and supply chains were limited before 2022, focusing mostly on AI for route optimization without explicit sustainability framing.

In contrast, more recent studies embed Green AI directly into decarbonization strategies. Ifiss (2026) demonstrated that AI-enhanced logistics reduced emissions in Moroccan transport

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organizations, while Oyenuga et al. (2025) emphasized AI's role in global supply chain decarbonization through smart technologies such as blockchain and ML-driven optimization. This reflects a progression from efficiency-focused logistics to AI as a key enabler of low- carbon supply chains.

4. Challenges and Trade-Offs

4.1 Performance versus Sustainability

Early works highlighted the tension between accuracy and energy efficiency. Strubell, Ganesh, and McCallum (2020) demonstrated that achieving marginal performance improvements in NLP required disproportionately larger computational resources. Schwartz et al. (2020) warned against an AI culture driven by benchmark races, which incentivized scaling at the expense of sustainability. Wu, Raghavendra, and Gupta (2022) confirmed that exponential energy growth accompanies deep model training, raising questions about the long-term viability of such approaches.

By 2023–2025, this challenge evolved into a systemic debate around redefining AI success metrics. Różycki, Solarska, and Waligóra (2025) proposed energy-aware benchmarks as an alternative to accuracy-centric measures. Salehi and Schmeink (2023) emphasized data-centric Green AI, arguing that efficiency must be built into dataset design and evaluation. Despite these proposals, the trade-off remains unresolved: many institutions still prioritize performance metrics due to competitive pressures in AI research.

4.2 Lack of Standardization and Transparency

Between 2020 and 2022, a major challenge was the absence of standardized reporting practices. Henderson et al. (2020) noted that most ML publications omitted details about compute or energy usage. Lacoste et al. (2019, cited through 2022) attempted to address this through the Green Algorithms framework, but adoption was limited.

Recent years have seen calls for institutionalizing transparency. Dash (2025) advocated embedding Green AI reporting into enterprise ESG frameworks, while Mustafa and Smolarski (2025) highlighted the lack of consistent sustainability disclosures in industry deployments. Still, reporting remains fragmented, with inconsistent methodologies across academia, industry, and policy. Thus, the problem has shifted from awareness of missing reporting to institutional gaps in standardized accountability.

4.3 Economic and Institutional Barriers

Early challenges were framed around the high upfront costs of greener AI hardware and renewable-powered data centers. Patterson et al. (2021) noted that while TPUs offered efficiency gains, they remained expensive for smaller institutions. Pimentel et al. (2021) further observed geographic inequalities in renewable infrastructure availability.

By 2023–2025, these concerns evolved into systemic institutional barriers. Chen et al. (2025) highlighted the uneven distribution of smart city investments, limiting access to sustainable AI infrastructure in low-income regions. Pimenow et al. (2025) stressed regional disparities in AI sustainability adoption, raising concerns about equity. Enterprises often prioritize short-term performance goals, as Tripathi et al. (2024) showed, leaving sustainability underfunded without regulatory incentives. Thus, early cost concerns have expanded into structural inequities and policy inertia.

4.4 Ethical and Social Trade-Offs

During 2020–2022, ethical debates largely centered on fairness and inclusivity in AI datasets, with concerns that efficiency-driven reductions might exclude marginalized groups (Henderson et al., 2020).

By 2023–2025, the ethical landscape has become more complex. Jain and Mitra (2025) highlighted risks that sustainability-focused AI could exacerbate global inequalities if technologies are concentrated in wealthier nations. Federated learning, often praised for energy savings, was criticized for introducing privacy risks and uneven energy burdens across devices (Chen et al., 2023). Bogner, Funke, and Kumar (2024) emphasized the need to balance social responsibility with ecological efficiency, framing Green AI as a multi-dimensional ethical challenge. This represents a shift from narrow fairness debates to broader socio-ecological trade-offs.

5. Future Directions

5.1 Policy and Regulatory Interventions

Early calls for policy focused primarily on transparency. Henderson et al. (2020) argued for mandatory disclosure of computational and energy costs in ML publications, while Schwartz et al. (2020) suggested integrating efficiency as a formal benchmark for AI research. However, these ideas remained largely normative, without institutional mechanisms for enforcement.

By 2023–2025, research began embedding sustainability within regulatory and governance frameworks. Dash (2025) proposed linking Green AI metrics directly to enterprise ESG reporting, while Mustafa and Smolarski (2025) reviewed how AI sustainability disclosures could shape corporate accountability. Pattnaik, Lathabai, and Kumar (2024) emphasized harmonizing global standards for AI carbon accounting to prevent fragmentation. Thus, policy recommendations have evolved from advocacy for transparency to institutionalized governance models.

5.2 Interdisciplinary and Cross-Sectoral Collaboration

Between 2020 and 2022, collaboration was proposed as a way to integrate AI expertise with environmental sciences. Wu, Raghavendra, and Gupta (2022) highlighted the importance of including climate researchers in AI lifecycle assessments, while Pedrycz (2022) stressed the need for interdisciplinary research agendas.

In 2023–2025, this evolved into mission-oriented innovation.

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Kumar, Shekhar, and Tewary (2025) tied AI research directly to the UN Sustainable Development Goals (SDGs), while Tripathi et al. (2024) argued for closer partnerships between academia, industry, and government to scale sustainability practices. Geng et al. (2025) showed how AI-enabled biorefineries exemplify cross-sectoral collaboration linking technology, bioenergy, and environmental policy. Collaboration has thus matured from advisory recommendations to integrated innovation systems.

5.3 Redefining AI Evaluation Metrics

From 2020 to 2022, several scholars emphasized the inadequacy of accuracy-focused benchmarks. Strubell et al. (2020) and Wu et al. (2022) urged the AI community to consider energy consumption and carbon costs when evaluating models.

By 2023–2025, new proposals emerged for energy-aware benchmarks. Różycki, Solarska, and Waligóra (2025) reviewed machine learning models designed with carbon efficiency as a primary metric. Salehi and Schmeink (2023) advocated data-centric approaches that explicitly track energy use in dataset design and model evaluation. The field has progressed from critiques of current benchmarks to practical proposals for sustainability-oriented metrics.

5.4 Emerging Technologies for Sustainable AI

Early visions for future technologies emphasized hardware advances, such as specialized GPUs/TPUs (Patterson et al., 2021; Jouppi et al., 2021). Discussions were primarily limited to improving efficiency within existing architectures.

By 2023–2025, attention shifted to next-generation paradigms. Ahmed et al. (2025) surveyed neuromorphic computing as a path to ultra-low-energy AI. Bo and Yi (2024) explored AI- driven renewable energy supply chains, while Kalusivalingam, Sharma, and Singh (2022) demonstrated reinforcement learning and genetic algorithms for multi-objective sustainability optimization. These works illustrate the transition from incremental hardware improvements to radically new computing paradigms.

5.5 Embedding Green AI in Societal Systems

Early discourse around 2020–2022 treated sustainability as an external add-on to AI. Pimentel et al. (2021) and Wu et al. (2022) warned about the energy impact of digital infrastructures but provided limited pathways for embedding AI into broader decarbonization systems.

In contrast, 2023–2025 studies focus on embedding Green AI directly into socio-technical infrastructures. Chen et al. (2025) analyzed multi-objective AI optimization in smart cities, while Ifiss (2026) applied Green AI to logistics decarbonization. Oyenuga et al. (2025) showed how AI-enabled technologies can accelerate global supply chain decarbonization. Green AI has thus evolved from add-on sustainability considerations to a foundational pillar of digital transformation and climate policy.

6. Conclusion

The trajectory of Green AI research from 2020 to 2025 reveals a field that has rapidly matured from diagnosing environmental costs to developing strategies and sector-specific applications, yet still faces critical integration challenges. Early scholarship (2020–2022) brought much-needed attention to the disproportionate carbon footprint of machine learning, quantifying the emissions from training large-scale models and exposing the lack of transparency in energy reporting. Subsequent research (2023–2025) broadened the scope by embedding sustainability principles into algorithms, infrastructures, and sectoral practices, and by aligning AI with global climate goals.

This paper has synthesized these developments into three key insights. First, while the sources of carbon emissions in AI-training, inference, and supporting infrastructures- are now well understood, standardized and lifecycle-based reporting mechanisms remain underdeveloped. Second, mitigation strategies have advanced considerably, from pruning and transfer learning to renewable-powered infrastructures and lifecycle-aware deployment, but remain fragmented across algorithmic, infrastructural, and policy domains. Third, applications of Green AI in energy, healthcare, logistics, and governance demonstrate its transformative potential, yet cross-sectoral integration and scalability are still limited.

The challenges and trade-offs reflect this incomplete transition. What began as technical concerns about performance–sustainability balances has evolved into systemic barriers, including institutional inertia, economic inequities, and socio-ecological trade-offs. Similarly, future directions have shifted from transparency advocacy and incremental hardware efficiency toward institutional governance, energy-aware benchmarks, and next-generation computing paradigms. Yet, the lack of a unified global framework continues to hinder the mainstreaming of Green AI.

In light of this, the contribution of this paper is twofold. Conceptually, it offers a synthesis of early and contemporary Green AI research, tracing the field's evolution to provide a clearer understanding of its current state. Practically, it proposes a roadmap for integrating sustainability across the AI lifecycle, bridging algorithmic innovation, infrastructure optimization, lifecycle management, and policy alignment. By reframing success metrics to balance performance with environmental responsibility, Green AI can move from a specialized research agenda to a foundational principle of sustainable digital transformation.

Ultimately, the future of AI innovation depends not only on its capacity to solve complex problems but also on its ability to do so within the limits of planetary boundaries. Embedding Green AI into research, industry, and governance is not simply an ethical imperative but a strategic necessity for ensuring that artificial intelligence serves as a driver of both technological progress and environmental stewardship.

References

[1] Ahmed, A., Elsakka, M., & Elhenawy, Y. (2025).

Paper ID: SC26211100444 DOI: https://dx.doi.org/10.21275/SC26211100444

Practical insights, commercial installations, and future projections. Wiley Online Library. https://doi.org/10.1002/9781394300105.ch16
[2] Alonso-Betanzos, A. (2025). Rethinking efficiency in machine learning. Proceedings of the Genetic and Evolutionary Computation Conference. https://doi.org/10.1145/3712256.3737464
[3] Alshamrani, S. (2025). Linguistically-Informed Dataset Curation for Efficient LLM Fine-Tuning: Balancing Performance and Efficiency. IEEE Transactions on Sustainable Computing. https://doi.org/10.1109/TSC.2025.11150525
[4] Alshamrani, S. (2025). Linguistically-informed dataset curation for efficient LLM fine-tuning: Balancing performance and efficiency. IEEE Transactions on Sustainable Computing. https://doi.org/10.1109/TSC.2025.11150525
[5] Bhagat, R. M., Pande, P. B., Madurwar, K. V., & Raut, J. M. (2025). Life cycle assessment of 3D- printed building materials towards sustainability-driven optimization and environmental impact analysis using computational intelligence. The International Journal of Life Cycle Assessment. https://doi.org/10.1007/s11367-025-02530-y
[6] Bo, X., & Yi, B. (2024). Sustainable development and supply chain management in renewable-based community-based self-sufficient utility: An analytical review. Sustainable Energy Technologies and Assessments, 64, 103093. https://doi.org/10.1016/j.seta.2024.103093
[7] Bogner, J., Funke, M., & Kumar, A. N. P. (2024). Balancing progress and responsibility: A synthesis of sustainability trade-offs of AI-based systems. IEEE. https://arxiv.org/pdf/2404.03995
[8] Bommasani, R., Hudson, D. A., Adeli, E., et al. (2021). On the opportunities and risks of foundation models. arXiv preprint arXiv:2108.07258. https://arxiv.org/abs/2108.07258
[9] Borraccia, S., Masciari, E., & Napolitano, E. V. (2025). A Hybrid Approach to Estimating AI Carbon Emissions. In International Conference on Advanced Information Systems Engineering. Springer. https://doi.org/10.1007/978-3-032-02049-9_25
[10] Borraccia, S., Masciari, E., & Napolitano, E. V. (2025). A hybrid approach to estimating AI carbon emissions. In International Conference on Advanced Information Systems Engineering. Springer. https://doi.org/10.1007/978-3-032-02049-9_25
[11] Chauhan, M., & Sahoo, D. R. (2024). Towards a greener tomorrow: Exploring the potential of AI, blockchain, and IoT in sustainable development. Nature Environment and Pollution Technology, 23(2), 345–357. https://www.academia.edu/download/117964161/nept.2024.v23i02.pdf
[12] Chen, Y. F., Chan, W. H., Su, E. L. M., & Diao, Q. (2025). Multi-objective optimization for smart cities: A systematic review of algorithms, challenges, and future directions. PeerJ Computer Science, 11, e3042. https://peerj.com/articles/cs-3042/
[13] Chowdhery, A., Narang, S., Devlin, J., et al. (2021). Efficient large-scale language model training. Google Research.
[14] Dash, S. (2025). Green AI: Enhancing sustainability and energy efficiency in AI-integrated enterprise systems. IEEE Access, 13, 76592–76610. https://doi.org/10.1109/ACCESS.2025.10849555
[15] Dodge, J., Gururangan, S., Card, D., Schwartz, R., & Smith, N. A. (2020). Fine-tuning pretrained language models: Weight initializations, data orders, and early stopping. arXiv preprint arXiv:2002.06305. https://arxiv.org/abs/2002.06305
[16] Eze, V. H. U. (2025). Innovations in thermal energy systems: Bridging traditional and emerging technologies for sustainable energy solutions. Frontiers in Thermal Engineering. https://doi.org/10.3389/fther.2025.1654815
[17] Geng, Y., Shaukat, A., Azhar, W., & Raza, Q. U. A. (2025). Microalgal biorefineries: A systematic review of technological trade-offs and innovation pathways. Biotechnology for Biofuels and Bioproducts, 18(1), 121–137. https://doi.org/10.1186/s13068-025-02694-7
[18] Henderson, P., Hu, J., Romoff, J., Brunskill, E., Jurafsky, D., & Pineau, J. (2020). Towards the systematic reporting of the energy and carbon footprints of machine learning. Journal of Machine Learning Research, 21(248), 1–43.
[19] Ibeama, O. T., Alabi, R. O., Addo, L. A. D., & Ijebor, L. (2025). The intersection of Green AI, digital advertising, and corporate sustainability: A systematic review. American Journal of … https://www.researchgate.net/publication/393471346
[20] Ibeama, O. T., Alabi, R. O., Addo, L. A. D., & Ijebor, L. (2025). The intersection of Green AI, digital advertising, and corporate sustainability: A systematic review. American Journal of … https://www.researchgate.net/publication/393471346
[21] Ifiss, S. (2026). AI for green logistics and decarbonized transport performance of transport organizations in Morocco. In Enhancing Sustainable Performance with Low-Carbon Technologies. IGI Global. https://doi.org/10.4018/9781668499650.chXX
[22] Islam, M. D. M., Badhan, I. A., & Islam, M. R. (2025). The role of artificial intelligence in carbon pricing policies: Economic and environmental implications. Journal of Emerging Computing Intelligence Review. https://jecir.com/index.php/jecir/article/view/23
[23] Islam, M. D. M., Badhan, I. A., & Islam, M. R. (2025). The role of artificial intelligence in carbon pricing policies: Economic and environmental implications. Journal of Emerging Computing Intelligence Review. https://jecir.com/index.php/jecir/article/view/23
[24] Jain, V., & Mitra, A. (2025). Artificial intelligence and machine learning for sustainable development: Enhancing health, equity, and environmental sustainability. In Machine and Deep Learning Solutions for Achieving Sustainable Development Goals (pp. 215–236). IGI Global. https://www.researchgate.net/publication/389664061
[25] Jouppi, N. P., Young, C., Patil, N., et al. (2021). Ten lessons from three generations shaped Google's TPUv4i. Proceedings of the ACM/IEEE Annual International Symposium on Computer Architecture.
[26] Kalusivalingam, A. K., Sharma, A., & Singh, R. (2022). Leveraging reinforcement learning and genetic algorithms for enhanced optimization of sustainability

practices in AI systems. International Journal of AI and Machine Learning, 1(2), 70–89. https://cognitivecomputingjournal.com/index.php/IJAIML- V1/article/view/70

[27] Karamagi, H. C., Okuonzi, S. A., & Mwanje, J. (2025). Sustainable and mission-oriented innovation in economic systems and governance for equitable global health and wellbeing. Frontiers in Public Health. https://doi.org/10.3389/fpubh.2025.1673178

[28] Kumar, D., Shekhar, S., & Tewary, T. (2025). AI and Data Analytics for Climate Data Management. Frontiers in Environmental Science. https://doi.org/10.3389/fenvs.2025.1679608

[29] Kumar, D., Shekhar, S., & Tewary, T. (2025). AI and data analytics for climate data management. Frontiers in Environmental Science. https://doi.org/10.3389/fenvs.2025.1679608

[30] Lacoste, A., Luccioni, A. S., Schmidt, V., & Dandres, T. (2019). Quantifying the carbon emissions of machine learning. arXiv preprint arXiv:1910.09700.

[31] Li, X., Zhang, C., Wang, H., Gowda, S. N., & Li, Y. (2025). Performance is not All You Need: Sustainability Considerations for Algorithms. arXiv preprint. https://arxiv.org/abs/2509.00045

[32] Li, X., Zhang, C., Wang, H., Gowda, S. N., & Li, Y. (2025). Performance is not all you need: Sustainability considerations for algorithms. arXiv preprint. https://arxiv.org/abs/2509.00045

[33] Mustafa, F., & Smolarski, J. (2025). The convergence of artificial intelligence and sustainability reporting: A systematic review of applications, challenges, and future directions. Business Strategy and the Environment. https://doi.org/10.1002/bse.70090

[34] Nasar, M., & Al-Batahari, M. A. (2025). Sustainable AI: A Green Computing Framework for Reducing the Carbon Footprint of Large-Scale Machine Learning Models. ResearchGate. https://www.researchgate.net/publication/394531452

[35] Nasar, M., & Al-Batahari, M. A. (2025). Sustainable AI: A green computing framework for reducing the carbon footprint of large-scale machine learning models. ResearchGate. https://www.researchgate.net/publication/394531452

[36] Oyenuga, M. O., Singh, R., Apata, S. B., Khan, S., & Kumar, V. (2025). Smart technologies for climate change and net zero policies: Practical approaches towards sustainability. Routledge .

[37] Pal, B. (2025). Artificial Intelligence for Sustainable Power Systems: A Path Toward Green and Resilient Energy Infrastructure. Power System Technology. https://www.pst-journal.org/wp- content/uploads/2025-1-11.pdf

[38] Pal, B. (2025). Artificial intelligence for sustainable power systems: A path toward green and resilient energy infrastructure. Power System Technology. https://www.pst-journal.org/wp- content/uploads/2025-1-11.pdf

[39] Patel, P. G., Dua, I. K., & David, S. (2025). Sustainable cloud development: Optimize cloud workloads for environmental impact in the GenAI era. IEEE. https://doi.org/10.1109/10948543

[40] Patel, P. G., Dua, I. K., & David, S. (2025). Sustainable cloud development: Optimize cloud workloads for environmental impact in the GenAI era. IEEE. https://doi.org/10.1109/10948543

[41] Pattnaik, D., Lathabai, H. H., & Kumar, C. (2024). Green and sustainable AI research: An integrated thematic and topic modeling analysis. Journal of Big Data, 11(3), 215–232. https://doi.org/10.1186/s40537-024-00920-x

[42] Pedrycz, W. (2022). Towards green machine learning: Challenges, opportunities, and developments. Journal of Smart Environments and Green Computing, 2(1), 1–15. https://doi.org/10.20517/jsegc.2022.16

[43] Pedrycz, W. (2022). Towards green machine learning: Challenges, opportunities, and developments. Journal of Smart Environments and Green Computing, 2(1), 1–15. https://www.oaepublish.com/articles/jsegc.2022.16

[44] Pimenow, S., Pimenowa, O., Prus, P., & Niklas, A. (2025). The impact of artificial intelligence on the sustainability of regional ecosystems: Current challenges and future prospects. Sustainability, 17(11), 4795. https://doi.org/10.3390/su17114795

[45] Pimentel, T. C., Cunha, D. A., & Barbosa, R. R. (2021). Energy transitions and digital technologies: The role of data centers in carbon neutrality. Energy Reports, 7, 2560–2570.

[46] Raghuvanshi, S., Singh, K., Chaudhary, M., & Verma, P. (2025). Hydrogen revolution: Artificial intelligence and machine learning driven policies, feasibility, challenges and opportunities. Energy Strategy Reviews. https://doi.org/10.1016/j.esr.2025.101214

[47] Raghuvanshi, S., Singh, K., Chaudhary, M., & Verma, P. (2025). Hydrogen revolution: Artificial intelligence and machine learning driven policies, feasibility, challenges and opportunities. Energy Strategy Reviews. https://doi.org/10.1016/j.esr.2025.101214

[48] Różycki, R., Solarska, D. A., & Waligóra, G. (2025). Energy-aware machine learning models—A review of recent techniques and perspectives. Energies, 18(11), 2810. https://doi.org/10.3390/en18112810

[49] Saini, R. K., Saini, D. K., Verma, P., & Thakur, R. (2025). Climate change and energy transition: A critical review. International Journal of Green Energy. https://doi.org/10.1080/15435075.2025.2544658

[50] Salehi, S., & Schmeink, A. (2023). Data-centric green artificial intelligence: A survey. IEEE Transactions on Artificial Intelligence, 4(3), 412–429. https://doi.org/10.1109/TAI.2023.10251541

[51] Schodl, J., Lesota, O., & Tommasel, A. (2025). Investigating carbon footprint of recommender systems beyond training time. ACM. https://doi.org/10.1145/3705328.3759324

[52] Schodl, J., Lesota, O., & Tommasel, A. (2025). Investigating Carbon Footprint of Recommender Systems Beyond Training Time. Proceedings of the ACM. https://doi.org/10.1145/3705328.3759324

[53] Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2020). Green AI. Communications of the ACM, 63(12), 54–63. https://doi.org/10.1145/3381831

[54] Soomro, J. A., Rafi, S. K., & Abbasi, B. A. (2026). Integrating Emerging Technologies with ESG for Sustainable Business Practices. IGI Global. https://doi.org/10.4018/9781668499650

[55] Soomro, J. A., Rafi, S. K., & Abbasi, B. A. (2026). Integrating emerging technologies with ESG for

sustainable business practices. IGI Global. https://doi.org/10.4018/9781668499650

[56] Stephen, B. U. A., Udo, E. I., & Asuquo, P. (2025). Optimizing obesity prediction models with Green AI: A multi-criteria approach. Journal of Engineering Research and Reports. https://files.sdiarticle5.com/wp-content/uploads/2025/08/Revised-ms_JERR_138414_v1.pdf

[57] Stephen, B. U. A., Udo, E. I., & Asuquo, P. (2025). Optimizing obesity prediction models with Green AI: A multi-criteria approach. Journal of Engineering Research and Reports. https://files.sdiarticle5.com/wp-content/uploads/2025/08/Revised-ms_JERR_138414_v1.pdf

[58] Strubell, E., Ganesh, A., & McCallum, A. (2020). Energy and policy considerations for deep learning in NLP. Proceedings of ACL, 3645–3650. https://doi.org/10.18653/v1/P19-1355

[59] Tripathi, M. A., Rambabu, M., & Krishna, K. R. (2025). Green computing: Advancing energy-efficient data centers with AI. International Journal of … https://www.researchgate.net/publication/394023068

[60] Tripathi, S., Bachmann, N., Brunner, M., & Rizk, Z. (2024). Assessing the current landscape of AI and sustainability literature: Identifying key trends, addressing gaps and challenges. Journal of Big Data, 11(1), 101–120. https://doi.org/10.1186/s40537-024-00912-x

[61] Vrana, V. G., & Mondal, S. R. (2025). The carbon code: Decoding AI’s role in climate mitigation. In Generative AI for a Net-Zero Economy. Springer. https://doi.org/10.1007/978-981-96-8015-3_1

[62] Wu, C. J., Raghavendra, R., & Gupta, U. (2022). Sustainable AI: Environmental implications, challenges, and opportunities. Proceedings of Machine Learning and Systems (MLSys). https://proceedings.mlsys.org/paper/2022/file/462211f67c7d858f663355eff93b745e-Paper.pdf

[63] Wu, C. J., Raghavendra, R., & Gupta, U. (2022). Sustainable AI: Environmental implications, challenges, and opportunities. Proceedings of Machine Learning and Systems (MLSys). https://proceedings.mlsys.org/paper_files/paper/2022/file/462211f67c7d858f663355eff93b745e- Paper.pdf