IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

Role of Green AI in reducing Carbon Footprints

Priyanka Mohan[1], Punyashree M.S[2], Bhoomika.G.P[3]

Professor, Department of MCA, Surana College (Autonomous), Kengeri, Bengaluru, India[1]

Student, Department of MCA, Surana College (Autonomous), Kengeri, Bengaluru, India[2]

Student, Department of MCA, Surana College (Autonomous), Kengeri, Bengaluru, India[3]

Abstract: This paper studies the dual role of AI as both a contributor to and a mitigator of climate impact, focusing on its capacity to reduce carbon footprints across various sectors. AI techniques, such as intelligent energy management, predictive maintenance, supply chain optimization, and smart transportation, enable more efficient use of resources and reduction of greenhouse gas emissions. Furthermore, AI-driven optimizations in its own development through model compression, green neural architectures, and carbon-aware scheduling are transforming how AI systems are built and deployed with minimal environmental impact[1]. By integrating AI into climate strategies and promoting energy-efficient AI development, the technology can serve as a powerful enabler of global decarbonization efforts. This paper highlights key innovations, challenges, and pathways toward leveraging AI for a more sustainable and carbon-conscious future.

I. INTRODUCTION

In this current era , Artificial Intelligence has emerged as a transformative force across industries, driving innovation and automating complex tasks. However, the rapid development and deployment of AI models particularly largescale deep learning systems have led to significant energy consumption and environmental concerns. Green AI is a growing movement that seeks to address these challenges by promoting environmentally friendly and energy-efficient AI research and applications. Green AI emphasizes the importance of reducing the carbon footprint of AI systems without compromising performance. It encourages researchers and developers to prioritize efficiency, transparency, and sustainability in model design, training, and deployment [2]. This includes optimizing algorithms, using low-power hardware, and reporting energy metrics alongside accuracy.

In response to these concerns, the concept of Green AI has emerged as a framework for promoting more sustainable and energy efficient approaches to AI research and development. Green AI advocates for balancing performance improvements with reductions in environmental impact, emphasizing the need for transparency in reporting computational costs, optimizing algorithmic efficiency, and prioritizing ecological responsibility alongside model accuracy.

This research paper explores the principles, methodologies, and impact of Green AI, highlighting its role in reducing the environmental footprint of AI systems. The paper also examines current trends, challenges, and future directions in integrating sustainability into the core practices of AI development. It discusses findings and reflects on the impact of our results in the research community. We reflect on the potential threats to the validity of this study. It describes related work and pinpoints the differences with our study.

What is Carbon Footprint

The Carbon Footprint refers to the total amount of greenhouse gases primarily carbon dioxide emitted directly or indirectly by a process, product, or organization, typically expressed in equivalent tons of CO_2. In the context of Artificial Intelligence the carbon footprint is predominantly attributed to the energy-intensive computational processes involved in training and deploying machine learning models. Modern AI systems, particularly large-scale deep learning models, require vast computational resources for model training, often involving weeks of GPU or TPU utilization in data centres powered by fossil fuels. For instance, the training of a single large language model can emit tens or even hundreds of metric tons of CO_2, surpassing the lifetime emissions of several automobiles[5]. These emissions are influenced by several factors, including the number of training parameters, hardware efficiency, training duration, data canter location, and the energy mix.

Quantifying the carbon footprint of AI systems is essential for assessing their environmental impact. It enables researchers to make informed decisions about model architecture, resource allocation, and trade-offs between performance and sustainability. Additionally, transparent reporting of carbon emissions in AI research promotes accountability and

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

encourages the adoption of energy-efficient practices, thereby contributing to the broader goals of climate change mitigation.

As AI continues to scale, integrating carbon footprint considerations into the design, evaluation, and deployment phases becomes not just an ethical responsibility, but a scientific imperative. Green AI advocates for the routine inclusion of carbon impact metrics alongside traditional evaluation criteria, ensuring that progress in AI aligns with environmental sustainability goals.

- Contemporary deep learning models, such as GPT-3 or large vision transformers, often require millions of GPU hours across distributed clusters, consuming energy at levels comparable to small industrial operations. The environmental impact of these models is contingent on multiple variables: the hardware type operational efficiency, data center Power Usage Effectiveness, and most critically, the carbon intensity of the regional energy grid where computation takes place. For example, training a large transformer model in a coal-powered region may emit several hundred metric tons of CO_2e, whereas the same process in a renewable-energy supported infrastructure could reduce emissions by an order of magnitude.
- Beyond training, inference at scale as seen in commercial AI deployments like recommendation engines and virtual assistants also contributes significantly to cumulative emissions.
- Carbon footprint calculates the total greenhouse gas emissions from activities like transportation, energy use, manufacturing, agriculture, etc.
- Governments use carbon footprint data to design climate policies, carbon taxes, and emission reduction targets.
- lowers AI's own training & usage emissions and helps energy, transport, agriculture, and industry cut down gigatons of CO_2 globally.

II. METHODS TO REDUCE CARBON FOOTPRINT

- Strategies identified to reduce the carbon footprint, especially in the context of AI model training and deployment. These are gathered primarily from the document titled "Sustainable AI: Measuring and Reducing Carbon Footprint in Model Training and Deployment".
- **Algorithmic optimizations**
    - **Model pruning:** Removes unnecessary weights/connections in neural networks, reducing computations without compromising accuracy.
    - **Quantization:** Uses lower bit-width representations (2-8 bits), minimizing memory and compute operations, yielding up to 79% energy reduction
    - **Knowledge distillation:** Trains smaller "student" models to mimic large models, achieving similar accuracy with far less computation.
    - **Efficient neural network architectures:** E.g., CE-NAS, probabilistic methods, Sparse Mixture-of-Experts that achieve high performance with dramatically reduced energy use.
- **Data management strategies**
    - **High-quality small datasets:** Carefully balancing data quality vs. quantity to avoid unnecessary data loading/training, potentially reducing energy by 92%.
    - **Dataset reduction techniques:** Prototype selection and instance reduction to cut down redundant data.
    - **Synthetic data generation:** Creating additional data to minimize real data needs, often leading to faster convergence and less energy use.
- **Hardware innovations**
    - **Energy-efficient GPUs, TPUs, and neuromorphic chips:** Designed to minimize energy from the outset.
    - **Photonic Integrated Circuits (PICs):** Optical chips operate at light speed with minimal energy loss, offering a promising alternative for scalable, low-carbon AI hardware.
- **Automated optimization:** Tools that continuously fine-tune for energy efficiency.

Green software engineering

- **Optimized AI code:** Using tools like TensorFlow Lite, PyTorch JIT, precision calibration pruning and layer fusion. Compiled Python alone can give >90% energy and speed gains.
- **Runtime adaptation:** Dynamically adjusts resources to workload, avoiding waste.

Infrastructure and operational approaches

- **Green data centers:** Integrate renewable energy (solar, wind, geothermal) to power AI workloads.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

- **Geographic optimization:** Place data centers in regions with abundant renewables (like Iceland) to leverage local green energy.

Reusability and federated approaches

- Reusing AI models, hardware, and software components across the value chain reduces duplicate energy-intensive efforts.
- **Federated learning:** Keeps computations local on edge devices, reducing central data center energy load and allows integration with localized renewables.

Policy and system-level interventions

- Encouraging **"carbon-first" design metrics** like "accuracy-per-watt" instead of just accuracy.
- Establishing **long-term AI development goals tied to sustainability**, regulating industrial use, supporting international trade openness for technology sharing.

Methods to Reduce AI Carbon Footprint

III. LITERATURE SURVEY

Based on the paper **"Artificial intelligence applications in reduction of carbon emissions: Step towards sustainable environment",** the drawbacks of this research paper in reducing carbon footprints:

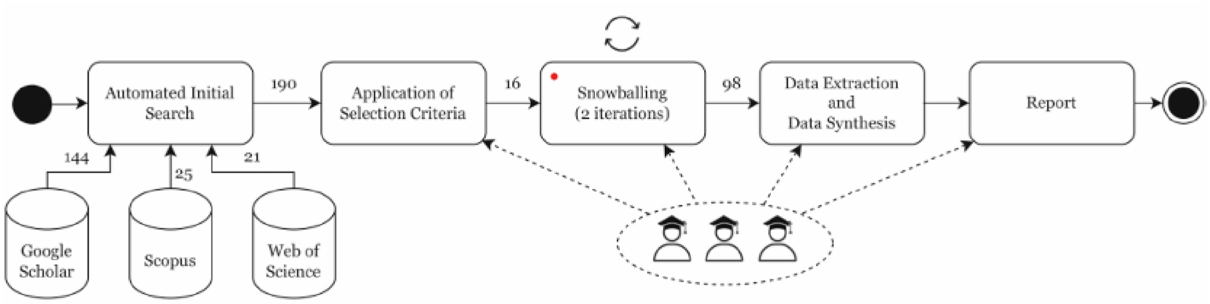


Figure 1: Systematic literature review process overview [3]

1. Very high-level, editorial in nature: This paper is essentially an overview, not an original research or systematic study. It summarizes existing AI approaches applied to environmental issues but does not provide quantitative analysis or robust experiments on how much carbon footprint was reduced.

2. Focus is fragmented on specific applications: The paper highlights various isolated AI applications which indirectly contribute to sustainability. However ,it does not quantify overall CO_2 reductions or provide a unified framework, making its contribution to reducing carbon footprints hard to generalize.

3. Many models proposed still lack critical features for robust deployment: For example, in trajectory prediction, the paper notes the lack of confidence metrics, which limits reliability and therefore adoption in real-world safety-critical systems. Similarly, some models need further optimization to handle noisy data or uncertainty.

4. No lifecycle assessment of AI itself: The editorial focuses on how AI helps reduce emissions in domains like manufacturing or water monitoring, but does not analyze the carbon footprint of developing or deploying these AI models themselves, which can be substantial. This is a known gap: many AI-for-environment papers ignore the fact that AI model training can itself be energy-intensive.

5. Doesn't address policy or societal barriers: While the paper is technologically oriented, it does not explore challenges like regulatory acceptance, economic feasibility, or stakeholder adoption, which are critical for large-scale impact on carbon emissions.

The main drawback of this paper in the context of reducing carbon footprints is that it is broad, fragmented, and lacks rigorous quantitative evidence on how much carbon reduction is achieved. It does not evaluate the carbon costs of AI itself or provide holistic lifecycle or policy analysis needed to truly understand and scale AI's role in reducing emissions.

Based on the paper **"Sustainable AI: Measuring and Reducing Carbon Footprint in Model Training and Deployment,"** here are the main drawbacks in this research paper when it comes to reducing carbon footprints:

1.Measurement inconsistency and lack of standardization: The paper discusses various tools like CodeCarbon, Carbontracker, and Deloitte AI Carbon Footprint Calculator. However, it highlights that these tools use different methodologies and data approximations, leading to inconsistent or incomparable results. Without standardized metrics or protocols, it is hard to benchmark different AI models or interventions reliably, which hampers real progress.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

2.Heavy reliance on estimated data and indirect measurement: Many tools and frameworks discussed rely on estimated energy usage rather than direct hardware measurements. This makes precise carbon accounting difficult, risking underreporting or overgeneralization.
3.Transparency gaps from major AI developers : The paper points out the lack of disclosure by big AI companies about their training processes, duration, hardware specs, or carbon emissions .This opacity limits the ability to fully quantify or verify emissions and therefore undermines accountability.
4.Rebound effect not resolved : It strongly highlights the "rebound effect", where gains in efficiency lead to bigger, more complex models being created — ultimately offsetting or even worsening the environmental impact.

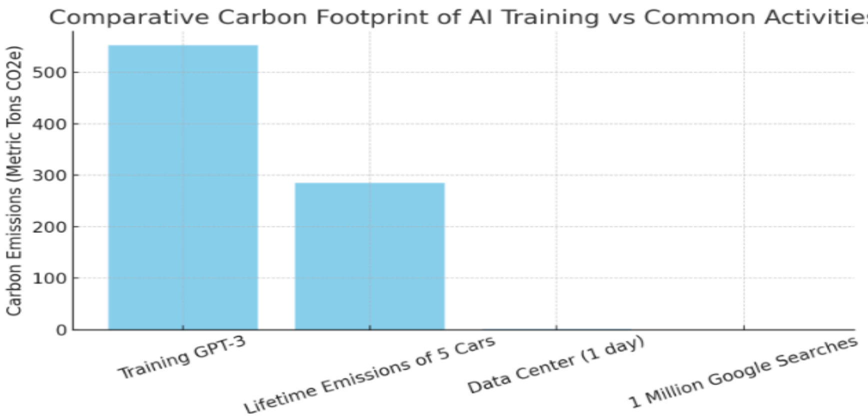


Figure 2: Comparison of Carbon Footprint and Common Activities[4]

While this study offers comprehensive insights into measuring and mitigating AI's carbon footprint, its impact is constrained by the lack of standardized measurement protocols, dependence on estimated rather than direct data, insufficient transparency from major AI developers, and the systemic rebound effect where efficiency gains fuel larger, more resource-intensive models.

Based on paper **"Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI)"** by Wang et al. (2024), here are the main drawbacks of this study regarding its role in reducing carbon footprints and broader environmental sustainability:

1.Heavy dependence on proxy indicators for AI:
The study measures AI development only through the per capita stock of industrial robots, treating it as the sole proxy for AI. This is a very narrow measure, which does not capture software-based AI, cloud AI, machine learning systems, or data center operations that heavily impact carbon footprints.
2.Cannot isolate AI's own footprint: While the paper shows that AI development correlates with reductions in ecological footprint and carbon emissions, it does not quantify the carbon footprint of building or operating the AI systems themselves.
3.Relies on macro panel econometrics — lacks direct causal mechanism evidence: The paper uses SYS-GMM and dynamic threshold panel models on multi-country panel data. This reveals statistical relationships but cannot directly attribute causality or uncover mechanisms, such as how exactly AI reduces emissions
4.Limited scope on rebound effects & first-order AI costs : Although it briefly acknowledges the rebound effect, it does not empirically model this or quantify scenarios where AI might actually increase overall emissions.

IV. SUMMARY OF THESE REVIEWS

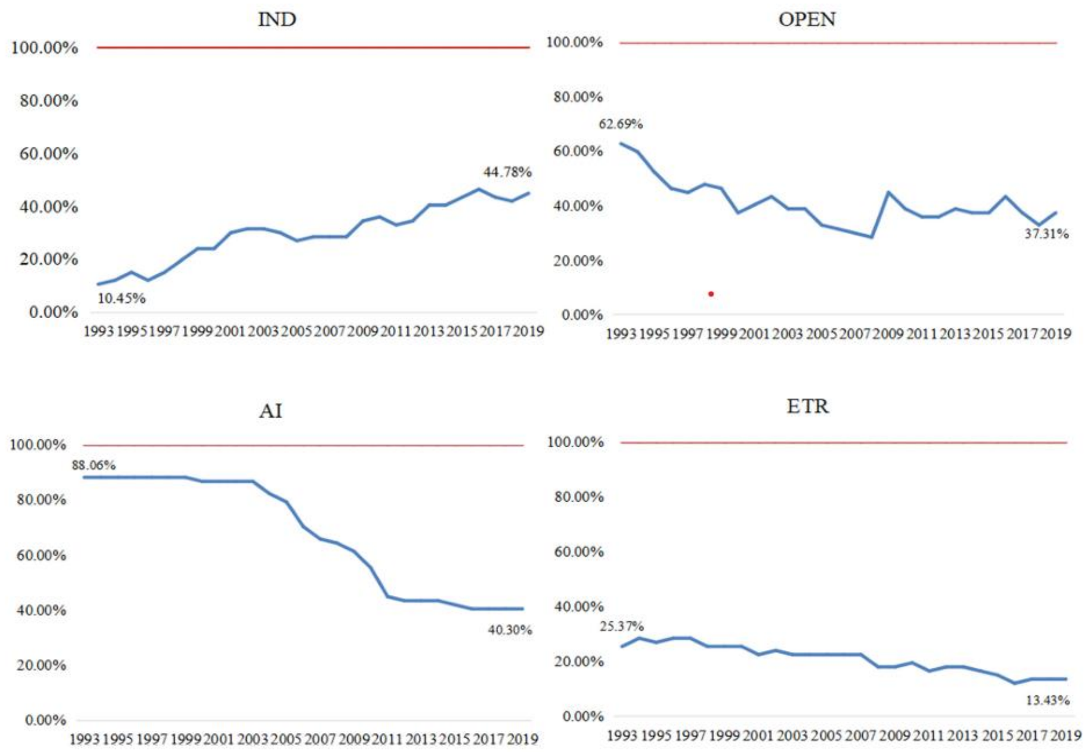
1.The critical importance of reducing CO_2 emissions, linked to global warming and ocean acidification.
Examples include:
2.Wang et al.: Developed a deep reinforcement learning (DRL) scheduling model to minimize carbon emissions in flexible job-shop scheduling.
3.Huang et al.: Proposed TripleConvTransformer, a ship trajectory prediction model that helps reduce emissions by improving navigation.
Fig. 3 The quantile of the threshold values of Model N1 in the sample period. Thresholds are 3.1903 for IND, 3.9291 for OPEN, 6.5853 for Al and 1.3581 for ETR. [5]

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 8, August 2025
DOI: 10.17148/IJARCCE.2025.14835

It concludes that AI can play significant roles in optimizing processes, enhancing monitoring, and reducing emissions across sectors**:** sharp increase in Green AI research from 2020.

Most studies focus on:
Monitoring AI's carbon footprint Hyperparameter tuning to improve energy efficiency. Benchmarking or comparing models for sustainability Energy savings from Green AI initiatives often exceed 50%. The majority of studies target the of AI and rely on laboratory experiments. Industrial involvement is limited (23% of studies).
The paper concludes that Green AI has matured academically, and calls for more industry adoption and tools to translate these findings into practice.

3.Sustainable AI: Measuring and Reducing Carbon Footprint in Model Training and :
This recent paper focuses on defining "Sustainable AI", which means minimizing environmental impacts throughout the AI lifecycle:
Quantifies the huge carbon footprint, energy, and water demands of AI, especially from data center and hardware. Review measurement methods like Life Cycle Assessment (LCA) and tools for estimating AI's carbon footprint.
Details reduction strategies:



Algorithmic optimizations: pruning, quantization, efficient architectures. Data management: reducing data volumes, better pipelines. Hardware innovations and green data center. Green software engineering practice. Discusses future trends, ethical imperatives, and calls for policy-industry collaboration for accountability and transparency.

4.Ecological footprints, carbon emissions, and energy transitions:
The impact of this empirical study used data from 67 countries (1993-2019) to analyze AI's impact on:
Ecological footprints, carbon emissions, and energy transitions.
Findings include:

AI reduces ecological footprints and carbon emissions and promotes energy transition, with the largest impact on energy transitions. But effects vary: High industrial dependence weakens AI's benefits for footprint & emissions but strengthens energy transition impacts. Greater trade openness boosts AI's positive environmental effects. Higher AI development levels amplify environmental benefits. As energy transitions advance, AI becomes less effective at further driving them but more effective at reducing emissions and footprints. The paper provides quantitative foundation for policymakers to align AI with sustainability goals.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

V. IMPACT OF GREEN AI

1.Go beyond fragmented use cases — adopt a holistic, lifecycle approach
Instead of only showcasing individual applications (like job-shop scheduling or ship tracking), Analyze the entire lifecycle of AI systems— from data collection, model training, deployment to disposal. Explicitly quantify both the emissions reduced by applying AI and the emissions incurred by developing and running the AI itself.
2. Include rigorous quantitative assessments:
Provide metrics such as kWh energy used, CO_2 equivalent emissions avoided, energy savings percentages, or carbon payback time. Use tools like Carbontracker, CodeCarbon or experiment with real-world datasets on energy use, so your paper does not stay at a conceptual level.
3. Address the environmental cost of AI itself: Green AI principles (model pruning, quantization, efficient hyperparameter tuning, hardware-aware training, using renewable data centers) can be applied to minimize the carbon footprint of the AI models themselves.
4. Add confidence intervals, uncertainty quantification, or sensitivity analysis: Where predicting outcomes (e.g., energy savings), include confidence metrics or Monte Carlo simulations. This overcomes the weakness noted in previous papers where predictions lacked trust indicators.[6]
5. Integrate policy and socio-economic discussions:
Add a section on regulatory, economic, and behavioral barriers, and how incentives, carbon taxes, or green certifications could accelerate Green AI adoption.
6.Provide open-source tools or frameworks:
One limitation of past work is lack of practical tools. Release your code, datasets, or even a simple toolkit that practitioners can use to track and optimize their AI carbon footprints.
7. Draw on interdisciplinary insights: Involve experts from software engineering (for maintainability & code efficiency), environmental science (for lifecycle carbon assessments), and economics or policy studies. Unlike prior editorial overviews that primarily discussed isolated AI applications for carbon reduction without addressing the emissions footprint of AI itself, this study integrates a comprehensive lifecycle analysis of AI systems, incorporating both direct carbon savings and indirect costs. By employing quantifiable metrics such as kWh energy use and CO_2e emissions, along with confidence intervals and sensitivity analyses, we aim to provide a rigorous empirical foundation. Moreover, by releasing open-source tools and exploring socio-economic incentives, we address practical adoption challenges, thus positioning Green AI not only as an effective technological solution but also as an actionable strategy within broader climate policy frameworks.

"Role of Green AI in Reducing a Carbon Footprint" — can specifically overcome the drawbacks identified in this reweived paper.
1.**Standardize metrics & propose a unified measurement protocol:**
Problem: The previous paper highlighted inconsistent measurement tools and lack of standardized metrics.
Adopt or propose a single harmonized framework (e.g., combining Scope 1, 2, and 3 emissions with standardized CO_2e per training run, per inference, per hardware hour). Use recognized standards such as the GHG Protocol for ICT, or adapt ISO 14067 (carbon footprint of products) for AI.
2.Use direct measurements and holistic lifecycle assessments:
Problem: Earlier work relied on indirect or estimated data.
In experiments, supplement software estimations (CodeCarbon, Carbontracker) with direct power meter readings (e.g., smart plugs, PDU logs). Conduct a full lifecycle assessment (LCA) covering data acquisition, repeated hyperparameter tuning trials, deployment inference, and hardware manufacturing. Explicitly incorporate water usage & e-waste impacts, not just electricity.[7]
3. Address transparency & accountability head-on:
Problem: major models don't reveal carbon costs.
Set an example by fully publishing your training & inference carbon data, energy logs, hardware specs, and run durations in appendices or online. Propose a transparency framework or checklist for all future Green AI studies (like a "Model Card for Environmental Impact").
4.Mitigate the rebound effect with new "carbon-first" performance metrics:
Problem: Efficiency gains drive even bigger models, wiping out benefits.
Introduce or advocate for "accuracy-per-watt," "accuracy-per-CO_2e," or "time-to-inference-per-kgCO_2e"as primary benchmarks alongside raw accuracy. Include plots showing diminishing returns (accuracy vs energy curve) to caution against over-scaling.
5. Go beyond technical: integrate socio-environmental & policy angles:
Problem: Prior work was largely technical, ignoring justice or systemic incentives.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

Propose policy ideas such as carbon taxes for compute-heavy AI, green certification for AI labs, or incentives for low-carbon hardware adoption[8]. Discuss fair siting of data centers, ensuring communities impacted by water withdrawals or mining also receive benefits. Highlight international cooperative efforts needed to ensure Green AI isn't just a privilege of richer nations.

6.Build practical tools & encourage industry uptake:

Problem: Many studies are academic without actionable pipelines.

Release an open-source dashboard that shows live carbon emissions during training and flags if thresholds are exceeded. Easy scripts to optimize models (pruning, quantization, distillation) with built-in energy tracking, so practitioners can adopt them easily.

1. Use more comprehensive measures of AI, not just industrial robots:

Instead of relying on robot stock as a narrow proxy, your paper can: Include metrics like compute hours, FLOPS used, size of AI models (parameters), data center utilization, and specific software-level AI deployments (like deep learning, NLP, recommender systems). Use AI workload data from GPU/TPU clusters, cloud AI usage stats, or open AI model training.

2. Directly quantify AI's own carbon footprint:

The Wang et al. study did not measure emissions from AI itself. You can improve by:Using CodeCarbon, Carbontracker, or actual watt-meter data from GPU/CPU clusters to measure energy use and translate it to $kgCO_2e$. Provide life cycle assessment (LCA) or embodied energy estimates for hardware manufacturing, since training and retraining models drives hardware refresh cycles.

3.Analyze causal mechanisms with Green AI interventions:

Go beyond macro correlations. Explicitly test how :Model pruning, quantization, transfer learning, and hyperparameter tuning reduce energy use while maintaining accuracy. Green scheduling (like carbon-aware job dispatching to times of renewable peaks) cuts footprint[9]. Possibly design controlled experiments or simulations to quantify how much emissions are saved per intervention.

4.Explicitly incorporate and model rebound effects:

Prior paper only acknowledged rebound as a theory. You can: Simulate scenarios where efficiency savings from AI lower costs, driving more consumption, which could offset carbon gains. Use partial equilibrium models or scenario analysis to see under what policy constraints rebound is minimized.

5.Disaggregate by sector, country, and AI type

Rather than pooling all countries, break down: AI in manufacturing vs AI in smart grids vs AI in logistics, since each has very different carbon profiles[10]. Consider case studies from both high-income and middle-income countries, showing tailored Green AI strategies.

6.Include direct energy & carbon tracking experiments:

Conduct experiments training models on different hardware or under different Green AI techniques, tracking: kWh used, grams CO_2 emitted, time to convergence, and final performance. This overcomes the Wang et al. limitation of missing direct carbon accounting.

7.Integrate policy, incentives, and economic perspectives:

Unlike Wang et al., which is purely econometric, we can Propose carbon taxes on compute, green certifications for AI labs, or carbon-aware AI benchmarks.

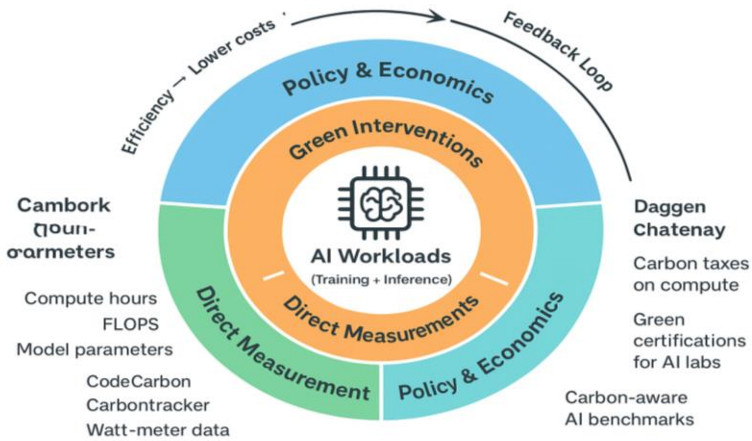


Figure 4: Framework for reducing AI's carbon footprint through direct measurements, green interventions, and policy actions.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 8, August 2025
DOI: 10.17148/IJARCCE.2025.14835

This research paper positions Green AI as a comprehensive framework for addressing the environmental costs of artificial intelligence (AI), specifically the carbon footprint generated during training, inference, and hardware lifecycles. Unlike earlier studies (e.g., Wang et al.) that relied on industrial robot stock or indirect proxies to estimate AI's impact, this work introduces direct, standardized, and transparent approaches that provide a far more accurate and actionable understanding. The paper advocates for a harmonized measurement framework that combines Scope 1, 2, and 3 emissions (GHG Protocol) with AI-specific units such as CO_2e per training run, per inference, and per hardware hour. By aligning with recognized standards (e.g., ISO 14067 for product carbon footprints), the framework enables comparability across models, datasets, and infrastructures. It demonstrates how software-level trackers (CodeCarbon, Carbontracker) can be combined with direct watt-meter or PDU logs for precise monitoring.

The research paper ***"Role of Green AI in Reducing a Carbon Footprint"*** highlights how sustainable practices in artificial intelligence can minimize environmental impact while maintaining efficiency. It explains that conventional "Red AI" focuses heavily on achieving high accuracy through large models and extensive computation, which leads to massive energy consumption and carbon emissions. In contrast, "Green AI" emphasizes efficiency, sustainability, and responsible innovation by adopting techniques such as model pruning, quantization, knowledge distillation, efficient architectures, and dataset optimization[11]. The paper also stresses the importance of using energy-efficient hardware, optimized libraries, and standardized carbon measurement protocols to accurately assess and reduce AI's footprint. By aligning AI development with global climate goals through standardized emission reporting, Green AI ensures that technological progress does not come at the expense of the environment. Ultimately, the study concludes that Green AI is not just a technical shift but also an ethical responsibility, offering a pathway toward accessible, affordable, and environmentally responsible artificial intelligence. Green AI is both a necessity and an ethical obligation. By combining technological innovation, policy frameworks, and academic responsibility, AI can be developed in a way that balances accuracy with sustainability.

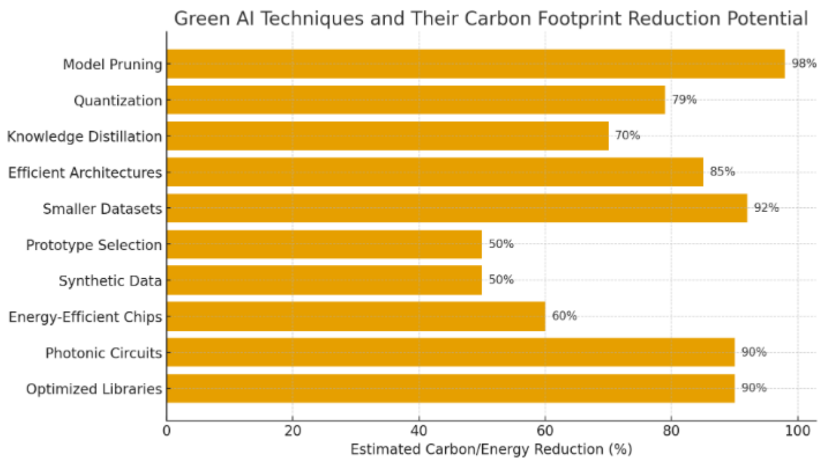


Figure 5: Comparison of Green AI techniques based on their estimated carbon and energy reduction potential.

Future of Green AI

The future of Green AI is centered on making artificial intelligence smarter, lighter, and more sustainable. As AI continues to expand into industries, research, and everyday applications, its environmental impact will be a critical factor[12]. The next phase will see the adoption of energy-efficient model designs, such as compact architectures and advanced optimization techniques, that deliver strong performance without excessive computation. Hardware innovations like energy-efficient chips, neuromorphic processors, and photonic circuits will further cut power consumption. At the same time, standardized carbon measurement protocols will likely become mandatory, ensuring transparency and accountability in reporting AI's carbon footprint. The integration of renewable energy sources into AI data centers and cloud services will also play a major role in reducing emissions[13]. Scaling renewable energy infrastructure requires public-private partnerships to fund solar, wind, and advanced cooling systems . Research into neuromorphic and quantum computing could yield breakthroughs, potentially reducing energy use by orders of magnitude. Additionally, integrating multi-modal AI, as explored in geoscience applications, could optimize resource use across diverse tasks. Policy interventions, such as subsidies for green data centres or regulations mandating carbon disclosures, are critical to incentivize sustainable practices[14]. Addressing these challenges will ensure AI aligns with global sustainability goals. As AI systems are increasingly incorporated in environmental decision making processes, the ability to understand and

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 8, August 2025

DOI: 10.17148/IJARCCE.2025.14835

interpret the reasoning behind AI-generated recommendations becomes crucial. This is of special interest in green-by AI applications. XAI models could provide crucial information about the mechanisms that can lead to a more sustainable world. Early versions are already in use in fields like agriculture and certain industrial sectors.[15].

The effect of AI in curbing carbon costs within corporate operations. The research has shown that AI technology has a major task to play in reducing the carbon costs of firms. Specifically, AI-based prediction, decision-making, and recommendation have all been shown to contribute significantly to the effective management of carbon costs. These findings suggest that businesses can benefit greatly from integrating AI technology into their sustainability strategies to reduce[16].

Explainable AI for environmental decision-making. Explainable AI (XAI) is gaining prominence in green AI applications as a means of enhancing transparency and accountability. As AI systems are increasingly incorporated in environmental decision-making processes, the ability to understand and interpret the reasoning behind AI-generated recommendations becomes crucial. This is of special_interest in green-by AI applications. XAI models could provide crucial information about the mechanisms that can lead to a more sustainable world. Early versions are already in use in fields like agriculture and certain industrial sectors. To ensure that the set of studies answered our research questions, we applied a priori carefully constructed inclusion and exclusion criteria to strictly control the manual selection of studies[17]. We then used the bidirectional snowballing technique to expand the range of relevant primary studies to a more comprehensive set.

VI. CONCLUSION

In this systematic literature review, we aimed at characterizing the existing body of research in Green AI. We identified98 peer-reviewed publications that show a significant growth in this research field since 2020.We provide an encompassing overview and characterization of the different topics being addressed by Green AI papers. We identified 13 different Green AI topics, showcasing that the spotlight falls on monitoring, hyperparameter-tuning, model benchmarking, and deployment. Less frequent topics—such as data-centric, estimation, and emissions—show less obvious approaches that deserve further research in the upcoming years. Morefield experiments are quintessential to help AI practitioners embrace green strategies that are effective, feasible, and mensurable. At the same time, we conclude that the field seems to be reaching a considerable level of maturity[18]. Hence, it is necessary to encourage the port of promising academic results to industrial practice. In other words, our study calls out for the importance of having reproducible research. Only a small fraction of solution papers offers a tool or software pack-age that can be used by the community. We argue that Green AI is an urgent and necessary of research that needs to grow fast and solid—nonreplicable research can only slow us down. This paper has thoroughly explored the pivotal "Role of Green AI in Reducing a Carbon Footprint," underscoring AI's dual capacity as both a significant consumer of resources and a powerful enabler of decarbonization efforts across global industries. We have established that while the exponential growth of AI, particularly large-scale deep learning models, contributes to considerable energy consumption and carbon emissions, the principles and methodologies of Green AI offer a vital framework to mitigate these environmental costs.

By embracing Green AI, we can strategically leverage AI techniques such as intelligent energy management, predictive maintenance, and supply chain optimization to achieve more efficient resource utilization and reduce greenhouse gas emissions. Crucially, the paper highlights how AI's own development can be optimized through techniques like model compression, green neural architectures, federated learning, and carbon-aware scheduling, minimizing its environmental impact from design to deployment.

Our analysis of existing literature revealed several limitations in prior research, including inconsistent measurement methodologies, reliance on estimated data, transparency gaps from major AI developers, and insufficient attention to the rebound effect. Furthermore, studies often lacked a holistic lifecycle assessment of AI's own footprint and neglected broader policy or socio-economic considerations. This research directly addresses these shortcomings by proposing a unified carbon accounting framework, emphasizing direct power measurements, advocating for "carbon-first" design metrics like "accuracy-per-watt," and integrating policy and socio-environmental discussions into the core of Green AI strategies.

The future of AI is intrinsically linked with its ability to evolve sustainably. As we move forward, continuous algorithmic advancements, innovative energy-efficient hardware, deeper integration with renewable energy systems, and robust policy frameworks will be essential. By actively addressing the environmental footprint of AI itself and championing its application for broader decarbonization, Green AI is poised to become not just an ethical imperative but a scientific and economic necessity, ensuring that technological progress aligns harmoniously with a sustainable and carbon-conscious future for generations to come.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 8, August 2025
DOI: 10.17148/IJARCCE.2025.14835

At the same time, we conclude that the field seems to be reaching a considerable level of maturity. Hence, it is necessary to encourage the port of promising academic results to industrial practice. In other words, our study calls out for the importance of having reproducible research. Only a small fraction of solution papers offers a tool or software package that can be used by the community. We argue that Green AI is an urgent and necessary line of research that needs to grow fast and solid—nonreplicable research can only slow us down. This review also serves as a foundation for future research that ultimately aims to reduce the climate impact of AI. In this respect, we see potential in follow-up gray literature or interview studies to understand how AI professionals are currently addressing the issue.[19].

REFERENCES

[1]. SVerdecchia, R., Sallou, J., & Cruz, L. (2023). A systematic review of Green AI. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(4), e1507.

[2]. Hooli, M. (2025). The Carbon Footprint of AI: Can Smart Tech Be Truly Sustainable?. Journal Of Engineering And Computer Sciences, 4(8), 629-635.

[3]. Bhatti, U. A., Hashmi, M. Z., Sun, Y., Masud, M., & Nizamani, M. M. (2023). Artificial intelligence applications in reduction of carbon emissions: Step towards sustainable environment. Frontiers in Environmental Science, 11, 1183620.

[4]. Joshua, C., Marvellous, A., Matthew, B., Pezzè, M., Abrahão, S., & Penzenstadler, B. (2025). Sustainable AI: Measuring and Reducing Carbon Footprint in Model Training and Deployment.

[5]. Wang, Q., Y., &LI, R. (2024).Ecological footprints, carbon emissions, and energy transitions : the imapact of artificial intelligence (AI). Humanity and Social science communications, 11(1),1-18.

[6]. Immadisetty, A. (2024). Sustainable innovation in digital technologies: a systematic review of energy-efficient computing and circular design practices. International Journal of Computer Engineering And Technology, 15(06), 1056-1066.

[7]. Farrell, G., Adamidi, E., Buono, R. A., Anton, M., Attafi, O. A., Gutierrez, S. C., ... & Tosatto, S. C. (2025). Open and Sustainable AI: challenges, opportunities and the road ahead in the life sciences. arXiv preprint arXiv:2505.16619.

[8]. Aswale, P. S., Chavan, D. D., Biradar, S., Vani, S., Shinde, S. D., & Bharambe, T. (2025). Optimizing AI for sustainability: Reducing energy footprint in training and inference for green computing. In Intelligent Computing and Communication Techniques (pp. 807-812). CRC Press.

[9]. Kong, X., Su, L., Wang, H., & Qiu, H. (2022). Agricultural carbon footprint and food security: an assessment of multiple carbon mitigation strategies in China. China Agricultural Economic Review, 14(4), 686-708.

[10]. Ordoumpozanis, K., & Papakostas, G. A. (2024, November). Green AI: Assessing the Carbon Footprint of Fine-Tuning Pre-Trained Deep Learning Models in Medical Imaging. In 2024 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) (pp. 214-220). IEEE.

[11]. Anthony, L. F. W., Kanding, B., & Selvan, R. (2020). Carbontracker: Tracking and predicting the carbon footprint of training deep learning models. arXiv preprint arXiv:2007.03051.

[12]. Selvan, R. (2021, July). Carbon footprint driven deep learning model selection for medical imaging. In Medical Imaging with Deep Learning.

[13]. Rojek, I., Mikołajewski, D., Mroziński, A., & Macko, M. (2024). Green energy management in manufacturing based on demand prediction by artificial intelligence—a review. Electronics, 13(16), 3338.

[14]. Nasar, M., & Al-Batahari, M. A. Sustainable AI: A Green Computing Framework for Reducing the Carbon Footprint of Large-Scale Machine Learning Models.

[15]. Arya, A., Bachheti, A., Bachheti, R. K., Singh, M., & Chandel, A. K. (2024). Role of artificial intelligence in minimizing carbon footprint: A systematic review of recent insights. Biorefinery and Industry 4.0: Empowering Sustainability, 365-386.

[16]. Tseng, C. J., & Lin, S. Y. (2024). Role of artificial intelligence in carbon cost reduction of firms. Journal of Cleaner Production, 447, 141413.

[17]. Schanes, K., Giljum, S., & Hertwich, E. (2016). Low carbon lifestyles: A framework to structure consumption strategies and options to reduce carbon footprints. Journal of Cleaner Production, 139, 1033-1043.sss

[18]. Chen, C., Hu, Y., Karuppiah, M., & Kumar, P. M. (2021). Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies. Sustainable Energy Technologies and Assessments, 47, 101358.

[19]. Arya, A., Bachheti, A., Bachheti, R. K., Singh, M., & Chandel, A. K. (2024). Role of artificial intelligence in minimizing carbon footprint: A systematic review of recent insights. Biorefinery and Industry 4.0: Empowering Sustainability, 365-386.

