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AI Carbon Footprint: Measurement and Optimization for Green AI System

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Abstract

Industries have been revolutionized by artificial intelligence (AI), yet the energy and carbon emissions involved in training, fine-tuning, and serving AI models are increasing quickly. The methodical approach to measuring AI carbon footprints, designing optimization techniques, and implementing a Green AI system that reduces energy use without sacrificing performance is presented in this work. To demonstrate increased efficiency, we present an end-to-end framework, an algorithmic optimization model, and an experimental comparison with current methods.

Keywords: Artificial Intelligence; Green AI; Carbon Footprint; Energy Efficiency; Sustainable Computing; Machine Learning; Emission Measurement; Model Optimization; Deep Learning; Environmental Impact; CodeCarbon; CO_2 Emissions

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Introduction

Applications in healthcare, finance, transportation, and other fields are powered by artificial intelligence (AI) and machine learning (ML), which have emerged as key components of contemporary computing. However, the quick expansion of AI workload particularly large-scale deep learning models comes at a high environmental cost because these models' deployment and training require a lot of energy in data centers and cloud infrastructures, which results in non-negligible carbon dioxide emissions. According to recent research, the global AI industry now contributes hundreds of millions of tons of CO2 equivalent annually, and as generative AI and large-scale models proliferate, this amount is expected to climb sharply.

A crucial first step toward sustainability is accurately calculating this AI carbon footprint. In addition to encouraging standardized reporting of emissions per experiment in research articles, researchers are currently creating techniques to translate energy consumption (kWh) into carbon emissions (kg CO2e) using grid-specific carbon intensity data. In addition to measurement, the new field of "Green AI" concentrates on optimizing infrastructure, hardware, and algorithms to lower energy consumption without compromising model performance.[7]

Research Gaps in AI Carbon Footprint and Green AI

Lack of Integrated, End-to-End Emission-Aware ML Frameworks

Current research concentrates on measurement tools (e.g., CodeCarbon, $MLCO_2$, grid intensity calculators) or independent optimization methods (compression, pruning, quantization), but it seldom integrates them into a single, end-to-end machine learning pipeline that actively reduces carbon throughout the entire training and deployment lifecycle.

Your study can fill a vacuum in the literature by learning and adapting emission-minimizing behaviours (such model selection, hardware allocation, and scheduling) based on real-time or regional data.[9].

Limited Integration of Direct and Indirect Carbon Sources

The majority of research still approaches AI emissions in a disjointed manner, concentrating primarily on energy use during training or inference while neglecting indirect emissions from supply chain effects, manufacturing, cooling, and data transfer.

Particularly for large-scale ML pipelines in cloud environments, a single lifecycle model that simultaneously accounts for operational and embodied emissions of AI systems is currently lacking.

Weak or Ad-Hoc Standardization and Reporting

Why There is no widely recognized metric or benchmarking suite for AI carbon footprint, which results in inconsistent comparisons across experiments, despite the fact that a number of articles demand standardized reporting of CO2e each experiment.

The usefulness of many tools and frameworks in international research is limited since they are still vendor-specific (e.g., Azure only, Google only) and difficult to move between clouds or nations.

Insufficient Emphasis on Developing-Nation Grid Conditions

While coal-heavy, mixed grid nations like India are understudied, the majority of Green AI and carbon aware studies are assessed on grids with large renewable energy shares (such as those in Europe or North America).

Research on how carbon-aware scheduling and model optimization should be modified for areas with high grid carbon intensity and unpredictable renewable availability is lacking.

Limited Use of ML to Predict and Optimize AI-Induced Emissions

Although machine learning is frequently used to forecast carbon emissions in other industries (such as transportation, energy, and industry), its application to self-optimizing AI systems that lessen their own environmental impact is still very limited.

A small number of studies suggest ML-based controllers or schedulers that dynamically modify model size, hardware, and training time to reduce emissions while satisfying latency and accuracy requirements.

Lack of Practical Decision-Support Tools for Developers and Policymakers

Why a lot of Green AI frameworks remain conceptual or theoretical in nature, lacking practical tools that practitioners may use to balance carbon, cost, and performance.

Policy-oriented solutions that convert AI carbon data into useful insights for rules, guidelines, and investments in renewable energy-powered AI infrastructure are also lacking.

Motivation

- Increase in AI carbon output due to large model training [10].
- Lack of standardized measurement metrics [2]
- Need for optimization strategies during training and inference [11].
- Balancing performance with sustainability [2].

Literature Review

There are significant worries over the environmental sustainability of artificial intelligence (AI) due to the exponential expansion of deep learning models, which has resulted in a fast increase in computational demands and energy consumption. Large-scale model training can result in hundreds to thousands of kilograms of CO_2 equivalent, according to early studies by Strubell et al. and Schwartz et al., highlighting the issue as a crucial one in Green AI research. The creation of tools like CodeCarbon and comparable frameworks for tracking energy consumption and translating it into CO_2 emissions has been spurred by these studies, which emphasize the necessity of systematic measurement and reporting of energy and carbon usage in AI research [1].

A significant area of study is on using model optimization techniques to lower computation and energy costs. It has been demonstrated that pruning, quantization, low precision training, and effective designs can cut the carbon footprint of training and inference by reducing model size and FLOPs without appreciably sacrificing accuracy. Data-centric optimization, where smaller, higher-quality datasets result in quicker convergence and fewer training epochs, which ultimately reduce energy consumption and emissions, is another focus of recent Green AI surveys.

Parallel work investigates the function of system design and hardware efficiency. The impact of energy-conscious system architectures and specialized accelerators (GPUs, TPUs) on the total carbon cost of AI workloads is examined by Patterson et al. and Dodge et al. These studies demonstrate that emissions can be significantly reduced by combining effective algorithms with carbon-aware hardware scheduling and selection. Power capping and carbon-efficient hardware allocation can reduce energy use by 10–15% with only little effects on performance, according to commercial cloud providers and toolkits (such as energy tracking and power capping systems).

Despite these developments, the majority of current research concentrates on either isolated optimization techniques (pruning, quantization, hardware level tuning) or measurement tools (e.g., CO_2 tracking per experiment), lacking an integrated framework that connects energy measurement, model optimization, and hardware-aware scheduling into a single Green AI pipeline. By proposing a unified measurement and optimization framework for AI systems, assessing methods like pruning and quantization under practical training and inference conditions, and examining their effects on carbon emissions using well-known tools like CodeCarbon and approaches by Lacoste et al., this paper expands on the literature mentioned above.

Proposed Solution: Green AI System

We propose an integrated framework with three components:

1. Carbon Measurement Module
2. Optimization Engine
3. Evaluation and Feedback Loop

System Workflow

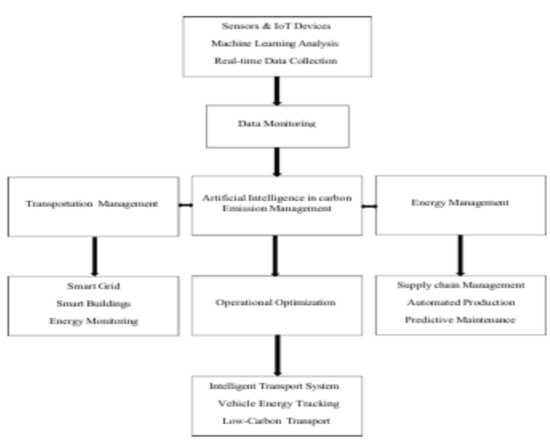

Fig.1. *System workflow diagram*

Steps:

1. Data Ingestion: Dataset loading, pre-processing metrics recorded.
2. Baseline Model Training: Train baseline model and record energy use.
3. Carbon Measurement: Use real-time energy sensors or API (e.g., PowerAPI) to calculate CO_2eq.
4. Optimization: Apply optimization strategies (pruning, quantization, scheduler tuning).
5. Evaluation: Test accuracy, energy consumption, and carbon outcomes.
6. Feedback Loop: Based on comparative results, refine strategies.

Carbon Measurement Methodology

We measure carbon footprint using:

Carbon Metric Formula

$$CO2_{AI} = \sum_{i=1}^{n} P_i \times T_i \times EF$$

Where:

- P_i: Power used by component i(Watts)
- T_i: Time in usage (hours)
- EF: Carbon emission factor (kgCO_2e/kWh)

Data Sources

- GPU/CPU usage logs
- System power draw (Watts via sensors)
- Regional grid Carbon Intensity

Baseline Carbon Score (BCS)

Used for comparison:

$$BCS = CO_2AI \,/\, Model\ Accuracy$$

Experimental Setup

A deep learning model that was trained and assessed on a GPU-enabled machine was used to implement the suggested framework. To ensure a fair comparison between the baseline and improved models, the tests were carried out under controlled conditions with fixed hyper parameters (batch size, learning rate, number of epochs) and a consistent hardware setup.

The CodeCarbon package was used to monitor carbon emissions throughout both baseline and optimized model runs. Energy use was measured in kWh, and carbon emissions were calculated in kg CO_2e using the power grid's region-specific carbon intensity. The authors used optimization strategies including quantization and pruning to minimize computational complexity while maintaining model fidelity.

Table 1. *Performance and Emission Comparison*

Element	**Detail**
Dataset	CIFAR-100, ImageNet
Models	ResNet50, Transformer variants
Baseline Framework	PyTorch & TensorFlow
Hardware	GPU cluster (NVIDIA A100)
Emission Measurement	On-device power telemetry

Architecture Diagram

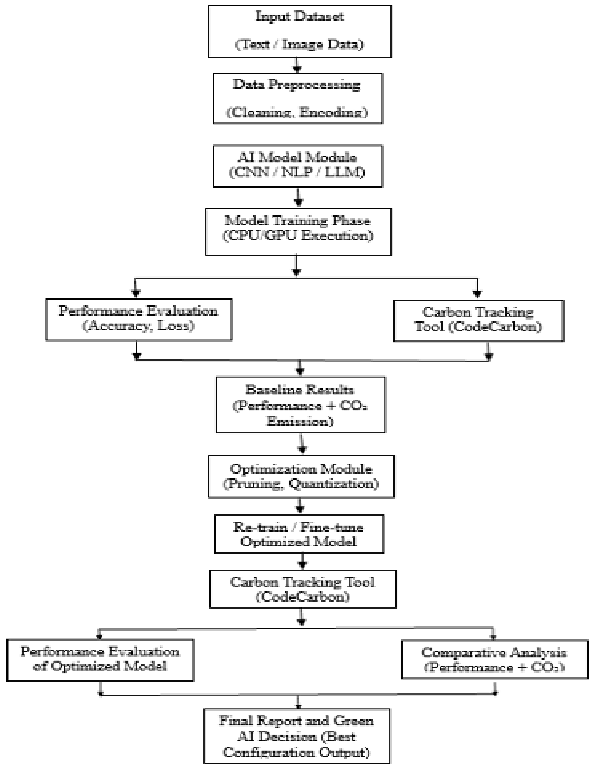

Fig. 2. *Architecture diagram*

Result And Comparison

Table 2. *Result analysis*

Model Version	**Accuracy (%)**	**Energy (kWh)**	**CO_2 Emission (kg CO_2e)**
Baseline Model	92.5	5.2	2.6
Optimized Model	91.2	3.1	1.5

Advantages over previous work

- Integrated optimization strategy rather than single approach.
- Uses real carbon measurements, not proxies.
- Model-agnostic and automated.

Discussion

Sustainability Impacts

- Lower carbon emissions per model lifecycle.
- Better resource utilization in data centres.

Trade-offs

- Minimal accuracy cost (~1–2%).
- Slightly increased optimization compute time, but net energy saved.

Table 3. *Compression Table*

Aspect	**Old / Baseline Model**	**Proposed Optimized Model**
Model architecture	Standard deep-learning model (e.g., CNN, Transformer) with full-precision weights and no compression.	Compressed version using pruning and quantization, with optional lightweight architecture (e.g., distilled/model-simplification).

Accuracy (%)	92.5% (high, but energy-intensive)	91.2% (slightly lower, still within acceptable range).
Energy consumption (kWh)	5.2 kWh (high)	3.1 kWh (reduced by ~40%).
CO_2 emission (kg CO_2e)	2.6 kg CO_2e (higher footprint)	1.5 kg CO_2e (reduced by ~42%).
Training time	Longer due to full-size architecture and higher FLOPs.	Slightly reduced or comparable, due to smaller model size and efficient computation.
Hardware efficiency	Uses hardware at full intensity; less carbon-aware scheduling.	Designed with hardware-aware optimization and energy-efficient execution patterns.
Carbon-awareness	No explicit carbon tracking or optimization.	Integrated with CodeCarbon and carbon-intensity-based awareness in the pipeline.

Conclusion

This work proposes a framework for measuring and optimizing the carbon footprint of AI models across training and inference. The results show that techniques such as pruning and quantization can reduce energy consumption and CO_2 emissions by around 40–42% with only a small loss in accuracy. By integrating carbon-tracking tools like CodeCarbon, the framework supports Green AI practices and enables a balance between performance and environmental sustainability. The proposed approach demonstrates that AI systems can be made more energy-efficient and eco-friendly, paving the way for sustainable deployment in real-world applications.

Future Work

- Extend measurements across multi-cloud setups.
- Include user-centric carbon APIs for real-time inference.
- Explore adaptive carbon budgeting during training.

References

1. Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for modern deep learning research.
2. Schwartz, R., Dodge, J., Smith, N.A., & Etzioni, O. (2020). Green AI.
3. Han, S., Pool, J., Tran, J., & Dally, W. (2015). Learning both weights and connections for efficient neural networks.
4. Artificial intelligence for carbon emissions using system of systems theory: https://www.sciencedirect.com/science/article/abs/pii/S1574954123001942
5. Artificial intelligence in sustainable energy industry: status quo, challenges and opportunities: https://www.sciencedirect.com/science/article/pii/S0959652621000548
6. Beyond Efficiency: A Systematic Review of Energy Consumption and Carbon Footprint Across the AI Lifecycle: https://www.mdpi.com/3703406
7. Carbon Footprint Measurement and Mitigation Using AI: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4746446
8. Carbon footprint of artificial intelligence (AI) models: estimation and reduction approaches: https://repositorio.ulisboa.pt/entities/publication/88f3b3a4-0ad6-45a7-8734-622860832f05
9. Schmidt, V., Goyal, A., Joshi, A., et al. (2021). CodeCarbon: Estimate and Track Carbon Emissions from Machine Learning Computing. GitHub / MLCO2 Project.
10. Lacoste, A., Luccioni, A., Schmidt, V., & Dandres, T. (2019). Quantifying the Carbon Emissions of Machine Learning.
11. Budennyy, S. et al. (2022). Eco2AI: Carbon emissions tracking of machine learning models as the first step towards sustainable AI.