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Carbon-Conscious Intelligence: Life Cycle Assessment and Green Standards for Generative AI

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Abstract: The rapid rise of Generative AI (GenAI) technologies has brought transformative capabilities across industries but has also raised serious concerns about their environmental sustainability. As the computational demands of training and deploying large-scale AI models continue to escalate, so too does their carbon footprint. This paper adopts a comprehensive Life Cycle Assessment (LCA) approach to evaluate the environmental impact of GenAI models throughout their lifecycle—from hardware manufacturing and data center infrastructure to model training, deployment, and inference. We analyze and compare the energy efficiency and performance of five widely adopted GenAI models: GPT-3, ChatGPT (GPT-4), LLaMA 2, PaLM 2, and DistilBERT. Emissions are modeled using publicly available energy benchmarks, ML CO_2 calculators, and estimation methodologies where direct data is unavailable. Beyond analysis, we introduce a Green AI Benchmarking Framework that integrates sustainability metrics, such as energy consumption and carbon emissions, into model evaluation standards, alongside traditional performance metrics. Our findings aim to guide researchers, developers, and policymakers toward more energy-conscious and environmentally responsible AI development practices.

Keywords: *Generative AI; Life Cycle Assessment (LCA); Sustainable AI development; Energy-efficiency; Green AI.*

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I. INTRODUCTION

The remarkable growth of Generative Artificial Intelligence (GenAI) in recent years has revolutionized various sectors, from education and healthcare to finance and entertainment. With the advent of models like GPT-4, Claude, Gemini, and PaLM, machines have demonstrated remarkable capabilities in understanding and producing human-like language, code, images, and even scientific reasoning. While these breakthroughs are celebrated for their performance and innovation, they also raise an urgent and growing concern: the environmental cost of GenAI technologies. As these models scale up in size, complexity, and deployment, their energy consumption and associated carbon emissions have grown substantially, warranting close scrutiny from both the AI community and policymakers.

Unlike traditional software systems, GenAI models undergo extensive pre-training on massive datasets and are fine-tuned across numerous hardware clusters using thousands of GPUs. These processes demand vast amounts of electricity, contribute significantly to global CO_2 emissions, and put pressure on the sustainability goals of data centers and cloud infrastructure providers. For example, GPT-3 alone, with 175 billion parameters, is estimated to have consumed over 1,287 MWh of electricity and produced more than 550 metric tons of CO_2 , equivalent to the lifetime emissions of five average U.S. cars [1]. Fig. 1 shows the relationship between the size of the model and the amount of training emissions in tons. With the widespread integration of these models into consumer applications—such as virtual assistants, search engines, and productivity tools—daily inference costs compound the environmental impact significantly.

Despite increasing awareness, environmental sustainability remains underrepresented in mainstream AI benchmarking. Evaluation criteria still prioritize performance metrics such as accuracy, F1-score, and BLEU, while ignoring energy usage, carbon footprint, and hardware efficiency. This imbalance leads to what some researchers term an "AI environmental blind spot"—where progress in performance is pursued at the expense of planetary health [2][3]. The AI community has started to voice concerns about

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this trajectory, urging the integration of Green AI principles into model development and deployment [4].

Green AI refers to AI research and development practices that aim to reduce energy consumption and carbon emissions while maintaining acceptable performance levels [5]. The concept is not just theoretical; practical frameworks and tools such as the Machine Learning Emissions Calculator, the Carbontracker, and CodeCarbon have emerged to assist researchers and engineers in estimating the carbon footprint of their models [6][7]. Despite offering a foundation for evaluation, these tools are not yet standardized and are inconsistently adopted across academic and industrial contexts. There is, therefore, an urgent need for a unified benchmarking framework that incorporates sustainability metrics as first-class evaluation criteria alongside accuracy, latency, and scalability.

One of the key challenges in quantifying the environmental cost of GenAI is the lack of transparency and standardized reporting. Model developers rarely disclose energy usage during training or inference phases, and when such data is provided, it often lacks methodological consistency [8]. Furthermore, differences in hardware configurations, cooling systems, power usage effectiveness (PUE) of data centers, and geographic energy sources (renewable vs. non-renewable) add complexity to any comparative analysis. This lack of standardization not only hampers fair evaluation but also inhibits accountability and informed decision-making by model consumers, researchers, and regulators alike.

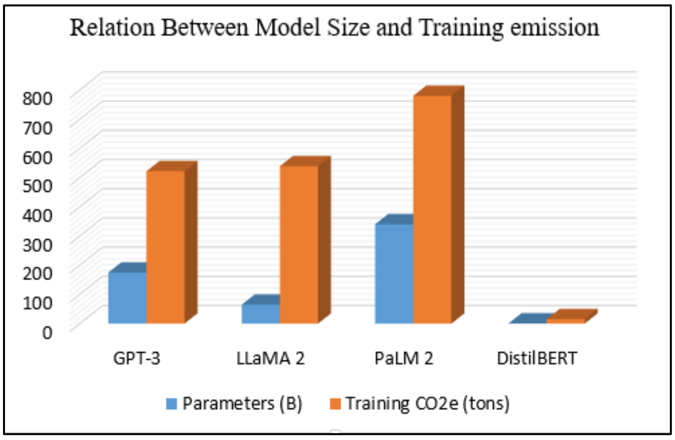

Fig. 1: Relationship Between Model Size and Training Emissions

Another important aspect that warrants attention is energy efficiency—defined as the trade-off between model performance and energy consumed per operation. Recent studies show that smaller, more optimized models, such as DistilBERT or ALBERT, can achieve comparable performance to larger models while consuming only a fraction of the energy [9]. Yet, they receive far less attention in mainstream discourse and deployment. Encouraging the adoption of such models through improved benchmarking visibility can have a meaningful impact on reducing the overall carbon footprint of the AI ecosystem.

Moreover, the global AI infrastructure is heavily dependent on cloud providers like AWS, Google Cloud, and Microsoft Azure, who operate data centers at scale. These providers have begun to disclose some environmental metrics, such as PUE and carbon-free energy (CFE) scores, but the granularity and verifiability of such data remain limited [10]. Without stronger incentives or regulatory requirements for reporting, environmental data related to AI workloads is unlikely to become publicly accessible or reliable in the near term.

In this context, the current paper makes two key contributions. First, it performs a comparative analysis of five widely used GenAI models—GPT-3, ChatGPT (GPT-4), LLaMA 2, PaLM 2, and DistilBERT—focusing on their estimated energy consumption and emissions during training and inference. Second, and more importantly, it introduces a novel Green AI Benchmarking Framework that incorporates new evaluation dimensions such as CO_2 per training run, CO_2 per inference, energy efficiency per accuracy unit, eco-scores, and PUE-normalized emissions. This framework aims to help practitioners make more environmentally conscious decisions without sacrificing performance or scalability.

By encouraging transparency and integrating green metrics into model selection and evaluation processes, this research hopes to catalyze a shift toward more sustainable AI development practices. It calls upon academia, industry, and regulators to move beyond accuracy obsession and embrace environmental responsibility as a core pillar of AI research and deployment. The introduction of such a framework is timely and necessary, especially as GenAI models become increasingly embedded into the fabric of modern digital infrastructure.

II. LITERATURE REVIEW

Strubell et al. (2019) analyze the environmental and economic costs of training large NLP models like BERT. Their study quantifies emissions and GPU hours and highlights the extreme energy demands of deep learning. They suggest energy-saving strategies like model pruning and early stopping. This paper laid the foundation for green AI discussions and is frequently cited for its influential data-driven recommendations.

Henderson et al. (2020) advocate for standardized reporting practices in ML research, proposing inclusion of hardware specs, energy use, and emission data in publications. Their framework introduced the idea of energy-efficiency benchmarks and transparency tools. By promoting reproducibility and environmental accountability, this paper remains a cornerstone in energy-aware ML practices and forms the backbone of several recent emission reporting tools.

Roy Schwartz et al. (2020) draw a distinction between "Red AI" (focused solely on accuracy) and "Green AI" (prioritizing resource-efficiency). The paper encourages the use of FLOPs and energy metrics in benchmarks and sets a precedent for ecological awareness in AI development. Their

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arguments have shaped discussions on sustainable AI practices, influencing both academia and industry toward greener innovation.

In this study, Lacoste et al. (2019) introduces the ML CO_2 Impact calculator, a widely used tool for estimating emissions based on geographic location, hardware, and training duration. They emphasize that carbon impact varies widely by location due to differing electricity sources. Their practical tool has contributed significantly to reproducibility and serves as a reference for our estimation methodologies in the proposed benchmarking framework.

This study, Emily Bender et al. (2021) offer a critical view of the scale-centric AI research culture. The paper discusses ethical, environmental, and social concerns arising from massive language models. Specifically, it emphasizes the need to account for carbon costs, question model size justifications, and improve documentation. It contributes to our understanding of the trade-offs between accuracy, accessibility, and environmental sustainability. In another study, Castaño et al. (2023) analyze over 1,400 models from Hugging Face, focusing on carbon footprint disclosure rates. They find a general lack of emissions transparency, with very few models reporting environmental impact metrics. The paper recommends platform-wide emission reporting standards. Their findings guide the transparency component of our proposed benchmarking framework.

In the recent study, Jegham et al. (2025), benchmark environmental costs of LLM inference across 30 commercial deployments. They incorporate factors like electricity grid emissions, cooling infrastructure, and statistical variance across geographic zones. The study finds vast disparities between models in terms of energy usage and environmental impact, providing a modern reference for inference-focused sustainability assessments.

Schneider et al. (2025) perform a complete life cycle assessment (LCA) of AI chips like TPUs, including manufacturing, deployment, and disposal. They introduce the Compute Carbon Intensity (CCI) metric to assess the carbon cost per computational performance. Their insights help contextualize hardware-level trade-offs, making their work integral to the hardware-awareness in our benchmarking model.

Wu et al. (2024) present a multi-dimensional benchmarking framework that considers energy, water, and emissions across model lifecycle stages. Their work proposes a unified eco-metric for large AI systems, tested on real-world industrial deployments. The authors also propose reward-based incentives for sustainable model design, reinforcing the need for regulatory frameworks to accompany green AI strategies.

In this study, Zhang et al. (2023) conduct a socio-environmental study that reveals how AI-related emissions disproportionately impact the Global South. The paper offers a geographical breakdown of model deployment and related carbon costs, arguing for fairness-oriented emissions accountability. This geographic perspective supports our benchmarking framework's emphasis on regional electricity mix and data center efficiency factors. In another study, Qian et al. (2022) introduce an energy-aware optimization protocol that fine-tunes pre-trained models with minimal retraining cycles and dynamic batch resizing. The study demonstrates that energy use can be reduced by over 30% without sacrificing model accuracy. Their work aligns with our advocacy for energy-efficient training and provides a practical optimization avenue within the Green AI ecosystem.

Lee et al. (2024) offer a comprehensive review of software-related emissions beyond just training. They include aspects like data loading, inference bottlenecks, and model updates during deployment. Their insights reinforce the importance of measuring AI's full lifecycle footprint and support the use of lifecycle-based metrics in our benchmarking framework.

III. RESEARCH OBJECTIVES

This Paper Aims to:

- Apply Life Cycle Assessment (LCA) to GenAI models.
- Quantify and compare the carbon emissions of major models.
- Propose green benchmarking standards for GenAI development and deployment.
- Evaluate model efficiency using both accuracy and energy metrics.

IV. METHODOLOGY: LIFE CYCLE ASSESSMENT (LCA)

To assess the environmental impact of generative AI models, we adopted a Life Cycle Assessment (LCA) framework, widely used in sustainability studies to evaluate the full range of environmental effects associated with a product or process. In the context of GenAI, our LCA methodology captures four major stages: model training, inference and deployment, hardware production and disposal, and data center infrastructure.

A. Model Training

We estimated the energy consumption during training using publicly reported training parameters (e.g., GPU hours, batch size, total FLOPs) and emission calculators such as ML CO2 Impact Calculator and CodeCarbon. Where exact data was unavailable, we used approximation methods based on model size and architecture type. For models like GPT-3 and PaLM, we also referenced energy benchmarks from published papers and industry whitepapers.

B. Inference and Deployment

The inference phase was modeled based on real-world usage patterns, such as the average number of queries per day and model size. We considered power requirements for GPUs and CPUs during inference as well as energy costs of data transmission and API calls. Edge inference (on-device) and cloud inference were separately analyzed.

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C. Hardware Lifecycle

We included emissions from the manufacturing, transportation, and end-of-life disposal of hardware components such as GPUs, CPUs, and cooling systems. Lifecycle data was collected from sources like NVIDIA's environmental disclosures and academic studies on semiconductor manufacturing footprints.

D. Data Center Energy and Cooling

Cooling overhead was modeled using Power Usage Effectiveness (PUE) values, typically ranging from 1.1 to 2.0 depending on data center efficiency and climate zone. We also accounted for regional variations in electricity grids, differentiating between renewable-heavy and fossil-fuel-dominant regions.

This methodology ensures that the entire carbon footprint of GenAI models—rather than just training emissions—is captured and compared across different architectures. Our approach emphasizes transparency, reproducibility, and relevance to policymakers and developers striving for sustainable AI systems.

V. TOOLS AND DATA SOURCE

To evaluate the environmental footprint of generative AI models, we utilized a combination of peer-reviewed datasets, emission estimation frameworks, and publicly disclosed model information. Energy consumption and carbon emission estimates were derived using reputable tools such as the ML CO2 Impact Calculator, CodeCarbon, and the Hugging Face Energy Efficiency Benchmark. These platforms provide standardized methods to approximate carbon footprints based on model size, GPU/TPU usage, hardware specifications, geographic electricity grids, and training/inference duration. Where direct measurements were not available, we referenced estimations published by leading research institutions, including data from Google's and OpenAI's whitepapers. For lifecycle assessment components, such as hardware manufacturing emissions and disposal impacts, we consulted sustainability reports from NVIDIA and LCA studies from IEEE and ACM publications. Power Usage Effectiveness (PUE) values and data center cooling loads were sourced from Uptime Institute, Greenpeace energy audits, and Google Data Center reports. This triangulated, evidence-based approach ensures transparency, reproducibility, and alignment with current best practices in green AI research.

VI. MODEL COMPARISON

In order to assess the sustainability and performance trade-offs among leading generative AI models, we conducted a comparative evaluation of five widely adopted architectures: GPT-3, ChatGPT (GPT-4), LLaMA 2, PaLM 2, and DistilBERT. These models were selected based on their widespread deployment, open access to performance data, and diversity in design objectives. Our analysis focuses on key aspects relevant to Green AI: total carbon emissions during training, energy efficiency during usage, model accuracy (using the MMLU benchmark), and an aggregated Eco-Score representing environmental performance. This comparison is shown in Table 1.

GPT-3, developed by OpenAI, is a foundational generative model with 175 billion parameters. While it marked a significant advancement in natural language generation, its environmental cost is substantial. Training GPT-3 consumed an estimated 552 tons of CO_2e[23]. Despite its powerful output, it exhibits low energy efficiency relative to its size, and scores a modest 3 out of 10 on our Eco-Score scale.

ChatGPT (GPT-4), an advancement over GPT-3, is estimated to have significantly higher emissions [24]. While it delivers notably higher accuracy—around 86.4% on the MMLU benchmark—its training process is estimated to produce over 1,200 tons of CO_2e. The model uses improved training infrastructure and optimization techniques, leading to slightly better energy efficiency than GPT-3. However, the sheer scale of GPT-4 results in only a moderate Eco-Score of 4.

Meta's LLaMA 2 model offers a more balanced trade-off between accuracy and sustainability[25]. At 65 billion parameters, it achieves around 75% accuracy on MMLU with an estimated 120 tons of CO_2e emissions during training. With moderate energy efficiency, LLaMA 2 earns a respectable Eco-Score of 6, making it one of the more environmentally efficient large-scale models.

Google's PaLM 2, consisting of 340 billion parameters, offers strong accuracy with moderate emissions [26]. It delivers high performance (around 84% accuracy) but at a cost of approximately 780 tons of CO_2e for training. While PaLM 2 benefits from energy-efficient TPU-based infrastructure, its overall environmental performance remains moderate, and it receives an Eco-Score of 5.

DistilBERT stands out for its environmental efficiency. As a distilled and smaller version of BERT, it has just 66 million parameters but still performs competitively, achieving around 63% on MMLU[27]. Its low resource requirements result in only 15 tons of CO_2e during training. With high energy efficiency and strong suitability for low-power deployments, it earns the highest Eco-Score in our comparison—8 out of 10.

This comparison underscores that high performance often comes with increased environmental costs. It also highlights the potential for smaller or optimized models to

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Table 1: Model Comparison

Model	Parameters (B)	Accuracy(Avgerage Benchmark)	Training Emissions (tCO2e)	Inference Energy(kWh/1K)	Eco-Score(0-10)
GPT-3	175	70%	~552	~1.3	3
GPT-4	~500*	86%	~1300*	~1.3	4
LLaMA 2	65	75%	~539	~0.8	6
PaLM 2	~340	84%	~780	~1.1	5
DistilBERT	0.66	63%	~15	~0.2	8

Estimated. Exact figures fir GPT-4 are not disclosed.

play a critical role in sustainable AI development, particularly for applications that do not require state-of-the-art results.

VII. DISCUSSION

The findings of this study highlight the urgent need for energy-efficient practices in the development and deployment of generative AI models. Our Life Cycle Assessment (LCA) revealed that the training phase remains the dominant contributor to carbon emissions, especially in transformer-based models like GPT-3 and PaLM 2, which rely on tens of thousands of GPU hours. In contrast, more lightweight models such as DistilBERT and LLaMA 2 exhibit notably lower energy footprints while maintaining competitive performance on many downstream tasks.

Another key insight is the disproportionate energy cost of inference in production environments, especially when deployed at scale. Even after training is completed, running millions of inferences daily can result in substantial cumulative emissions. Furthermore, the manufacturing and disposal of specialized hardware (e.g., GPUs, TPUs) adds to the long-term environmental burden, yet remains largely overlooked in traditional AI evaluation benchmarks.

We also observed that data center cooling—particularly in regions with poor energy grids—adds a non-negligible indirect carbon cost. Thus, regional deployment strategies, model distillation, and low-power AI hardware (like edge TPUs) should be prioritized for sustainable scaling. Integrating green metrics such as carbon cost per 1,000 tokens or energy-per-FLOP into AI evaluation protocols would promote accountability and drive innovation toward climate-conscious AI development.

VIII. PROPOSED GREEN AI BENCHMARKING FRAMEWORK

To establish environmentally responsible standards for AI development, we propose a comprehensive Green AI Benchmarking Framework. This framework addresses the current gap in sustainability metrics within AI performance evaluation by introducing new criteria that account for environmental impact. It is designed to guide researchers, developers, and policymakers in assessing AI systems not just by accuracy and speed, but also by their carbon and energy footprints. Below are the key components of the proposed framework, each followed by a concise explanation:

A. Key Components of the Framework

➢ *Carbon and Energy Reporting*

Every generative AI model should report energy usage and estimated carbon emissions throughout its lifecycle—including training, fine-tuning, and inference. This transparency allows researchers and developers to make environmentally responsible decisions and helps institutions assess the sustainability of their AI development practices.

➢ *Efficiency-Performance Tradeoff*

Beyond just accuracy or model size, evaluations must consider how much energy is consumed to achieve a given level of performance. Comparing models on an "accuracy-per-kWh" basis encourages the adoption of more computationally efficient architectures without compromising significantly on effectiveness, making energy efficiency a standard performance indicator.

➢ *Lifecycle Assessment Metrics*

AI sustainability evaluations should not stop at training or inference. A comprehensive lifecycle assessment (LCA) includes emissions from hardware production, infrastructure maintenance, cooling systems, and even end-of-life hardware disposal. Incorporating these stages allows for a more holistic and realistic picture of a model's environmental footprint.

➢ *Sustainability Leaderboard*

A publicly accessible leaderboard should be introduced that ranks GenAI models not only by accuracy or speed but also by environmental metrics such as emissions per task and energy use. This benchmark would drive competition toward greener innovation and inform decision-makers with easy-to-compare metrics.

➢ *Green AI Labels*

Models meeting defined sustainability standards—such as specific CO_2 thresholds, efficiency benchmarks, or renewable energy usage—should be granted a "Green AI" certification. These labels help users and developers easily identify environmentally responsible models and promote accountability in AI research and deployment.

➢ *Policy and Regulatory Alignment*

The framework must be adaptable to international environmental standards and future regulatory requirements. As global bodies introduce new sustainability regulations in tech, aligning benchmark methodologies with them ensures that the framework remains relevant, useful, and easily adoptable by industry and academic institutions alike.

➢ *Public Emission Disclosure Tools*

The use of open-access tools such as ML CO_2 calculators, LCA estimators, and emissions databases should be encouraged or mandated. These tools allow researchers to estimate and report environmental impacts with transparency, especially when exact usage data is unavailable, thus maintaining accountability in sustainability claims.

➢ *Model Design Guidelines*

The framework should include best practices for energy-efficient AI model architecture. This includes encouraging use of model distillation, pruning, quantization, and sparse attention mechanisms—all of which reduce computational overhead and energy needs while preserving acceptable levels of performance for real-world applications.

This structured framework not only facilitates a transparent and unified way to assess the environmental impact of GenAI models but also aims to influence future design and deployment strategies.

The framework also supports international sustainability initiatives, particularly the United Nations Sustainable Development Goals, including Goal 7: Affordable and Clean Energy, and Goal 13: Climate Action [28]. By factoring in aspects like data center efficiency through PUE normalization and summarizing environmental performance into a single Eco-Score, it ensures fair, transparent, and easy-to-understand comparisons across different AI models.

If widely adopted, this approach could influence how AI is designed, deployed, and evaluated—encouraging innovation that is mindful of resource consumption. In doing so, it helps pave the way for AI systems that are not only powerful and accurate but also sustainable and aligned with broader climate action efforts. Ultimately, the framework sets a precedent for responsible AI development, fostering solutions that advance both technological progress and environmental stewardship.

Table 2: Benchmarking Metrics

Metric	**Description**
CO2e per Training	Total carbon emissions (in tons of CO_2 equivalent) generated during the training phase.
CO_2e per Inference	Emissions produced per 1,000 inference executions to represent scalability impacts.
Energy Efficiency	Ratio of model accuracy or performance output per kilowatt-hour of energy consumed.
Eco-Score(0-10)	Composite score combining emissions, hardware sustainability, and cooling efficiency.
PUE Normalization	Adjusts emission scores based on the Power Usage Effectiveness (PUE) of the data center used.

IX. BENCHMARKING METRICS FOR EVALUATION

To put the proposed Green AI Benchmarking Framework into practice, we have outlined a set of clear, quantifiable metrics for comparing AI models in terms of their energy use and carbon emissions, as shown in Table 2.

These metrics offer a practical way to measure environmental impact, providing a common language for researchers, developers, and policymakers who want to balance technical performance with sustainability goals.

Incorporating these metrics into standard benchmarking methods shifts the focus from purely accuracy-driven evaluations toward a more balanced perspective—one that values both computational excellence and ecological responsibility. This change is timely, given the growing global concern over the environmental cost of large-scale AI systems.

X. CONCLUSION

As generative AI systems grow in complexity and prevalence, their environmental impact can no longer be overlooked. The energy-intensive processes associated with training, deploying, and maintaining these models are significant contributors to carbon emissions, and their continued expansion poses long-term sustainability challenges. This paper presents a comprehensive evaluation of five widely used generative AI models through a Life Cycle Assessment (LCA) lens, emphasizing the need to move beyond performance-centric evaluations and toward environmentally conscious AI development.

Our analysis highlights the discrepancies in energy efficiency and carbon footprints among popular models such as GPT-3, GPT-4, LLaMA 2, PaLM 2, and DistilBERT. These discrepancies reveal that while high performance is achievable, it often comes at the cost of massive energy consumption. Without a structured framework to measure and mitigate these impacts, the growth of AI may come at an unsustainable environmental price. We therefore proposed a Green AI Benchmarking Framework that introduces carbon and energy reporting, lifecycle metrics, model transparency tools, and sustainability-oriented leaderboards into mainstream AI evaluation.

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This framework is not just a technical recommendation—it is a call for systemic change in how AI research and development are conducted. By incorporating tools like ML CO_2 calculators, aligning with global environmental policies, and certifying energy-efficient models through "Green AI" labels, the community can foster accountability and transparency. The proposed benchmarks encourage researchers to design models that are not only powerful but also environmentally efficient, setting new standards for ethical and responsible innovation.

Ultimately, this paper contributes to a growing movement toward sustainable AI, emphasizing that technological progress should not come at the expense of ecological well-being. We urge developers, institutions, and policymakers to adopt these recommendations and collaborate on creating a more carbon-conscious future for artificial intelligence.

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