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Research Article

The Real Environment Impact of AI: Unveiling the Ecological Footprint of Artificial Intelligence

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ARTICLE INFO	ABSTRACT

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Global environmental pollution has a devastating influence on the planet's population and jeopardizes humanity's future. The construction business is a major producer of waste and hazardous emissions into the atmosphere. It is vital to discover measures to reduce the damage done to nature. Currently, artificial intelligence technologies are one of the most promising approaches to helping the environment. This research investigates the use of green AI algorithms for measuring greenhouse gas (GHG) emissions in the context of ecological footprint assessment. Green AI algorithms prioritize sustainability and seek to lower AI systems' carbon footprints while monitoring GHG emissions data. These algorithms use environmentally conscious machine learning techniques to improve resource allocation, encourage energy-efficient model topologies, and prioritize renewable energy sources for AI model training. Carbon-aware optimization approaches are used to reduce the environmental impact of AI computations, resulting in a greener future. The incorporation of green algorithms into AI systems identifies the potential for emission reduction and energy efficiency, promoting environmentally beneficial behaviours across industries. The use of green algorithms allows for a full analysis of GHG emissions and ecological footprints, permitting a symbiotic interaction between technology and the environment for sustainable growth.

Keywords: Artificial Intelligence (AI), Ecological footprint, GreenHouse Gas (GHG), Natural Language Processing (NLP)

INTRODUCTION

Protecting the Earth's ecology is a critical concern in today's world. The devastation done to the environment has disastrous ramifications for humanity. Climate change causes fires, floods, droughts, and other natural disasters. Hazardous emissions also hurt human health. To reduce the detrimental impact, suitable environmental safeguards must be implemented. Artificial intelligence (AI) is the replication of human intelligence in robots designed to think and learn like humans [1]. AI includes a variety of techniques and technologies, such as machine learning, natural language processing, computer vision, and robotics. It allows computers to accomplish tasks that would normally need human intellect, such as comprehending language, identifying patterns in data, making decisions, and solving problems. The implications are mostly measured in the context of energy usage and greenhouse gas emissions. However, it's important to note that the environmental impact of these technologies extends beyond only energy use. [2] For example, it believes that AI systems will have a significant impact on the environment through their indirect effects on the global digital economy. According to [3], focusing just on profit and job stability without considering broader repercussions can have negative consequences for the future generations.

AI is gaining popularity and being promoted as an environmental solution issue, including Artificial Intelligence for Green initiatives [4][5].

AI's environmental costs are given to break the loop between Green and Green AI. Assessing impacts, both positive and negative, is crucial. There is a brief mention of the negative environmental repercussions of AI, including rebound effects [4], which can result in increased global GHG emissions. However, no assessment of allt the ecological footprint quantifies humanity's influence on Earth's resources, including the land and resources needed to support human life. It incorporates food, water, energy, and waste production, demonstrating sustainability. It evaluates environmental impact by comparing consumption to available resources, hence encouraging sustainable practices. A smaller footprint suggests less strain on ecosystems, which promotes biodiversity and environmental health [6].

Artificial intelligence has advanced so dramatically that it is currently regarded as the preferred method for addressing environmental challenges, especially greenhouse gas emissions. Meanwhile, those involved in deep learning began to understand that training models with an increasing number of parameters require an enormous quantity of energy and, as a result, increases GHG emissions. According to the understanding, no one has directly addressed the subject of the total net environment implications of Artificial intelligence for environmental solutions (Green AI), including GHG emissions. This essay, recommends investigating the potential detrimental implications of AI on Green. First, this discusses the many sorts of AI impacts, followed by the various approaches for assessing those impacts and demonstrating how to apply life cycle evaluation to AI services [7]. Finally, this explains how to evaluate the environmental utility of a general AI service and highlights the Green algorithm, Concurrently, the data centres that run AI technology release considerable amounts of carbon dioxide, exacerbating the environmental impact. Despite these obstacles, AI offers prospects for monitoring and mitigating environmental issues like deforestation and pollution. However, striking a sustainable balance between technology innovation and environmental preservation remains a pressing challenge, necessitating concerted efforts to promote greener AI development techniques [8].

LITERATURE SURVEY

This section discusses techniques for evaluating AI's environmental impact and green applications. The paper concludes with an overview of the carbon footprint of AI and LCA, a well-established method for evaluating environmental effects that is not commonly employed in Artificial Intelligence services.

2.1. Carbon Footprint of Artificial Intelligence

Strubell et al. [9] demonstrated the significant impact of NLP algorithms during training, resulting in GHG emissions comparable to 300 flights between New York and San Francisco. Premises of this technique were already included in [10] for CNN, although with less useful measures (e.g., energy per image or power without indication of global time).

In [11], the authors discover a broad exponential development in deep learning architecture parameters. They advocate a "Green AI" that prioritizes energy efficiency with correctness in training models and emphasizes the need to disclose floating-point processes. Other writers [12] have studied various strategies for estimating energy usage in computer architecture. The authors distinguish between various kinds of explanation, especially software/hardware and instruction/application, and explore how these methods could be used to monitor the training and inference phases in machine learning [13].

Several approaches have been postulated that highlight the influence of training models, building on [9] and [11] work. They can be schematically divided as

- Integrated tools: Python libraries, such as Experiment Impact Tracker 1, Carbon Tracker 2, and CodeCarbon 3, report energy use and carbon footprint.
- Online tools: Green Algorithms 4 and ML CO_2 impact 5 require a few parameters, including training length, material, and location, but have lower accuracy.

AI literature focuses on immediate effects and ignores production and end-of-life considerations, resulting in a lack of compliance with suggestions. In [14], the writers highlight. This study addresses methodological limitations in earlier studies focused on the usage stage. Manufacturing is responsible for approximately 75% of Apple's or iPhone 5's total emissions, depending on scale. The study follows a life cycle methodology and uses sustainability reports that meet the GHG protocol requirement. [15] lists the carbon emission sources of AI services, providing a complete assessment of their direct implications on the carbon footprint. It emphasizes the importance of considering indirect implications, such as behavioural or societal changes while evaluating AI services [16][17].

Some research focuses on improving artificial intelligence procedures for the runtime, energy consumption, and carbon footprint. In [18], the authors update the results from [9] and show a factor of 100 reductions in GHG impact by considering the location of the training data centre (low-carbon energy) and the deep network design (sparsity). The study focuses solely on GHG emissions from operating computers and data centres, disregarding manufacture and end-of-life phases.

2.2. Life Cycle Assessment (LCA)

Life Cycle Assessment is a popular method for ecological impact assessment, having ISO standards (ISO 14040 and 14044) and a specialized ICT approach guideline from ETSI/ITU [19]. It measures environmental standards throughout all life cycle stages of an intended system. Decisions should be made with a systems view to avoid problem shifting, which occurs when solving one problem leads to the creation of additional and sometimes overlooked problems. LCA is frequently utilized in several fields, but it has rarely been used in AI services [20].

METHODOLOGY

1.1. Evaluating the usefulness of Artificial Intelligence for green services.

When presenting an AI for Green technique, it is important to guarantee that the total ecological influence is positive. This means that the helpful gains from the solution should outweigh any negative implications. The AI service's first-order implications stem from the lifecycle phases of the equipment used for development and deployment, as discussed previously.

Second-order impacts refer to the effects of Artificial Intelligence. AI can improve or replace existing systems, such as optimizing energy use in buildings through habitation or behaviour recognition, energy profiling, and more.

Third-order consequences are modifications to technology or society caused by AI solutions. These effects may range from distinct behavioural reactions to systematic and social alterations and can be short-term or long-term. Rebound properties refer to when an improvement in effectiveness may not always result in a decrease of equal magnitude of impacts, and may instead enhance them. Rebound effects arise when potential savings e.g., money, time, and resources are converted into increased consumption. Smart occupants of buildings may choose to increase the heating temperature for convenience or purchase extra aeroplane tickets after achieving higher energy efficiency.

Assessing the utility of AI for green services requires a thorough examination of its effectiveness, efficiency, and impact on environmental sustainability. This evaluation examines if the service meets its intended objectives, such as optimizing resource utilization, lowering carbon emissions, and improving conservation efforts. Efficiency considerations include assessing resource use, time savings, and cost-effectiveness. Furthermore, analyzing the actual environmental impact entails calculating carbon emission reductions, energy efficiency gains, and conservation outcomes. Furthermore, user experience, long-term viability, and ethical implications all play important roles in determining the service's utility. By carefully examining these criteria, stakeholders may make better-informed decisions on the adoption and implementation of AI for Green services, resulting in a more sustainable and eco-friendly future.

1.2. Greenhouse Gas

Greenhouse gases (GHGs) are gases in the Earth's atmosphere that trap heat, causing the greenhouse effect and global warming. These gases are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases. When sunlight strikes the Earth's surface, some of it is absorbed and heats the globe, while the remainder is reflected into space as infrared radiation.

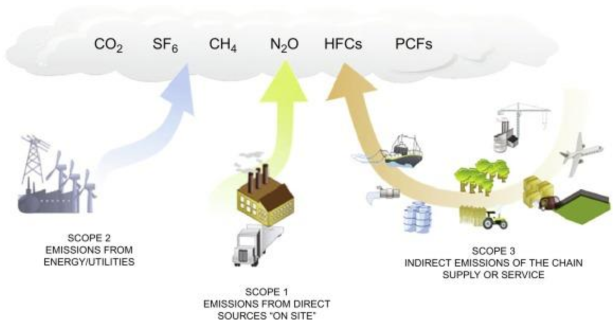

Figure 1: Greenhouse Gas

Greenhouse gases in the atmosphere absorb infrared light, preventing it from escaping into space and increasing the Earth's surface temperature. Human activities including fossil fuel combustion, deforestation, agriculture, and industrial processes have greatly boosted greenhouse gas concentrations in the atmosphere since the Industrial Revolution. This heightened greenhouse effect accelerates global warming, leading to climate change and its consequences such as rising temperatures, sea-level rise, and extreme weather events. Measuring and lowering greenhouse gas emissions is critical for combating climate change and maintaining the planet's health. Efforts to minimize emissions include switching to renewable energy, increasing energy efficiency, implementing sustainable agriculture methods, and safeguarding forests and other carbon sinks. By lowering greenhouse gas emissions, they may alleviate the effects of climate change and move toward a more sustainable future.

1.3. Using a Green algorithm for GHG emission

Using green AI algorithms to assess greenhouse gas (GHG) emissions in the context of ecological footprint requires the application of environmentally conscious machine learning approaches. These algorithms are intended to emphasize sustainability and lower AI systems' carbon footprint while assessing GHG emissions data. Green algorithms aim to reduce energy consumption during computation by optimizing resource allocation and encouraging environmentally friendly behaviours throughout the AI lifecycle. This emphasis on sustainability ensures that AI processes have a positive impact on the environment. These algorithms include ideas like energy-efficient model structures, which aim to save energy during model training and inference. For example, using sparse models or pruning approaches can reduce the processing resources required for AI activities, resulting in lower energy use.

Furthermore, green algorithms prefer renewable energy sources while training AI models. AI systems that use solar, wind or hydroelectric power for model training can reduce dependency on fossil fuels and the carbon emissions associated with energy generation.

Also, carbon-aware optimization techniques are used to reduce the carbon footprint of AI computations. These approaches analyze the environmental impact of various computational activities and select low-emission strategies to get the required results. By incorporating green algorithms into AI systems, opportunities for emission reduction and energy optimization are recognized. For example, AI can improve energy-intensive tasks like data processing or model training to reduce carbon emissions while preserving performance. Furthermore, green algorithms encourage ecologically friendly practices in a variety of businesses by giving insights and recommendations for sustainable operations. AI-driven energy management systems, for example, can optimize energy usage in buildings or industrial operations, resulting in lower GHG emissions.

1.4. Tools

1.4.1. Code-Based tools

Tools for measuring and computing the environmental impact of AI.

- CodeCarbon: Track and Compute emissions and make recommendations on how to lessen their environmental impact.
- CarbonTracker: Keep track of and anticipate the energy usage and carbon footprint associated with deep learning model training.

- Eco2AI: A Python package that collects statistics on power consumption and CO_2 emissions while running code.
- Zeus: A framework for deep learning-based energy assessment and optimization.
- Tracarbon: Tracks the device's energy use and calculates the carbon emissions based on the location.
- AIPowerMeter: Easily track the energy consumption of machine learning programs.

1.4.2. Monitoring tools

Tools for tracking electricity use and environmental implications.

- Scaphandre: A metrology agent focused on electrical power consumption measures.
- PowerJoular: Monitor power consumption across many platforms and processes.
- Baogent: Local API and tracking agent concentrated on the host's environmental effects.
- vJoule: A tool to calculate how much energy the processes use.
- Jupyter-power-usage: Jupyter addon to show carbon emissions and CPU and GPU usage of power.

RESULTS

It created a simple method for estimating an algorithm's carbon footprint based on a variety of criteria such as the tool's hardware requirements, runtime, and data centre location. Using a pragmatic scaling factor (PSF), improve the model by permitting empirical estimates of repeated computations for a specific job, such as parameter tuning and trial-and-error. The resulting gCO2e is compared to the amount of carbon stored by trees, as well as the emissions from everyday activities like driving and flying. It created Green Algorithms, a publicly available web application that implements the approach and allows users to evaluate their computations or estimate the carbon savings or costs of redeploying them on various architectures.

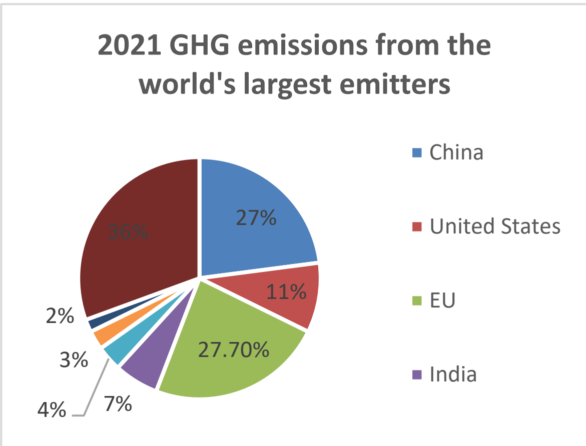

Figure 2: 2021 GHG emissions from the world's largest emitters.

In 2021, just eight big economies accounted for approximately two-thirds of global emissions (Figure 2). China remained the largest single contributor to global GHG emissions, accounting for 27% of total emissions, followed by the United States (11%), the European Union, and India (7%).

It uses this tool with algorithms from several scientific domains, including physics (particle simulations and DNA irradiation), atmospheric sciences (weather forecasting), and machine learning (NLP). For each work, for factors unrelated to the technique, It utilizes global average values, such as 1.67 for power usage effectiveness (PUE) and 475 gCO2e kWh−1.[27]

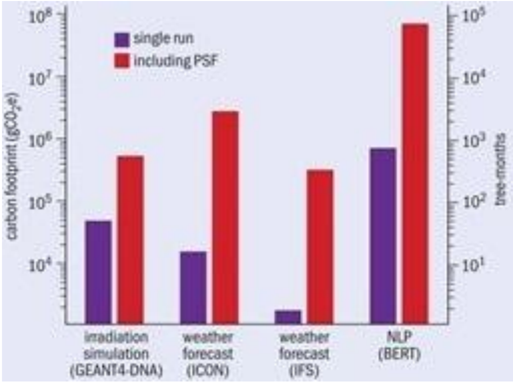

Figure 3: Carbon footprint (gCO_2e) of a variety of algorithms, with and without their pragmatic scaling factor.

4.1. Particle Physics Simulations

Simulations in particle physics, such as Geant4, model particle behave in the matter and are utilized in a variety of applications ranging from collider detectors to medical radiation analysis. Meylan et al. investigated DNA radiation damage with Geant4-DNA, doing studies at various photon energies. Using Green Algorithms, they projected that each experiment would release 49,465 gCO2e, for a total of 544,115 gCO2e with energy level variations. This equates to driving 3109 kilometres or fly from New York to San Francisco.

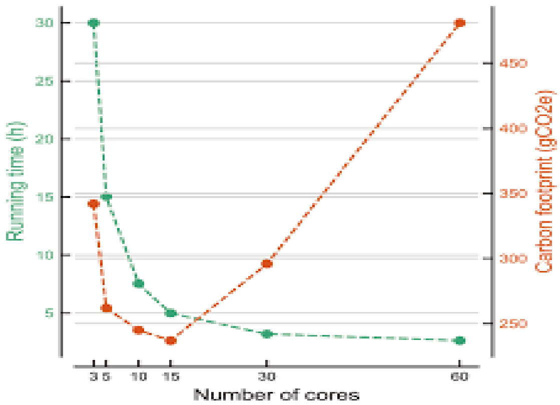

Figure 4: The impact of parallelization with several cores on running time and carbon footprint has been simulated using TestEm12 GEANT4.

The study's carbon impact corresponds to 593 months of CO2 emissions. Schweitzer et al. discovered that increasing processing cores up to 15 improved both runtime and emissions, but doubling cores from 15 to 60 increased emissions with minimal time gain, emphasizing the trade-off between runtime and GHG emissions in parallelized computations. Optimal core numbers minimize emissions for parallelized algorithms.

4.2. Weather Forecasting

Weather forecasting relies on complicated models that simulate interactions between Earth's components. Neumann et al. examine two models: the ECMWF's Integrated Forecast System (IFS) and DWD's Icon. IFS produces 10-day predictions with a 9-kilometre resolution, requiring 128 Broadwell nodes and releasing 1660 gCO2e every forecast day (FD). ICON, with a resolution of 13 km, requires 575 nodes and emits 12,848 gCO2e for each FD. Moving ECMWF supercomputing to Bologna could boost emissions by 18% due to Italy's greater carbon intensity. These emissions are similar to driving 1708 km, or three Paris-London return trips for IFS, and 13,215 km, or four New York-San Francisco flights for ICON, per day.

4.3. Natural Language Processing

The complexity and expense of model training provide important hurdles in Natural Language Processing (NLP). To solve this, language representations such as BERT have emerged. BERT provides great performance and versatility, enabling fine-tuning for specialized workloads such as academic analysis of text and biological text mining without requiring complete retraining. Despite BERT's objective to reduce training, most data scientists stay to enhance it, resulting in duplicate computation and increased CO2e emanations. Even with specialized hardware such as NVIDIA Volta GPUs, a BERT training run can last more than three days. Strubell et al. discovered that training BERT on 64 Tesla V100 GPUs for 79 hours produced 754,407 gCO2e. With hyperparameter search, this rises to 75,440,740 gCO2e. Additionally, Google's Meena, a chatbot program, was trained for 30 days on a TPU-v3 Pod with 2048 TPU cores and an estimated power supply of 288 KW. Meena's training produced 164,488,320 gCO2e, the equivalent of 179,442 tree-months or 71 New York-Melbourne flights. These findings highlight the environmental impact of training advanced NLP models and emphasize the importance of sustainable computing methods in AI research and development.

DISCUSSION

The approach and Green Algorithms tool given here offer users a realistic way to calculate the carbon footprint of their computations. The method focuses on creating reasonable estimates with low overheads for scientists looking to quantify the environmental impact of their work. As a result, the online calculator is easy to use and applicable to almost any computational work. It used the Green Algorithms calculator to estimate relative and ongoing carbon emissions from a variety of jobs, including particle physics simulations, weather forecasting, and natural language processing. Everyday life, modifications to computing structures, such as shifting data centres, were also quantified in regards to carbon footprint and demonstrated to be of significant relevance, moving data centres, for example, may result in a higher PUE, but variations in CI may cancel out any efficiency benefits, thereby harming the environment.

The findings greatly improve existing methods for assessing computation's carbon footprint by incorporating and formalizing previously confusing aspects like core use and unitary power draw. This enables a more exact breakdown of an algorithm's carbon footprint into clearly quantifiable components such as core count and memory consumption. By streamlining the procedure, users no longer have to manually measure hardware power drain or rely on a restricted number of cloud providers. In comparison to earlier approaches, the solution provides greater flexibility. In addition to raising awareness about greenhouse gas emissions from data centres, the precise approach and technology aim to enable users to reduce their carbon footprint. Establishing common practices for estimating and reporting is a significant difficulty in green computing GHG emissions, which the Green Algorithms calculator and open-source resources address, promoting transparency and accessibility.

The technique has some drawbacks. To begin, it simply assesses the carbon footprint of GHGs emitted during computer operation, disregarding the total life cycle impact of hardware manufacturing, maintenance, and disposal, as well as power plant maintenance. Including these components is impractical on a large scale. Second, the conversion of various GHGs to CO2e may misrepresent short-lived climate pollutants such as methane. Third, the Thermal Design Power (TDP) may underestimate power consumption, especially in hyperthreading settings. Fourth, strong reliance on storage queries can greatly increase power consumption, albeit this is usually minimal for single computations. Fifth, differences in a country's energy mix can have an impact on emissions estimates, and the Power Usage Effectiveness (PUE) indicator for data centres is limited due to inconsistencies in calculation techniques. Finally, carbon emissions estimates are based on manual literature curation, with assumptions made where data is lacking, leading to potential discrepancies with actual emissions.

CONCLUSION

The implementation of green AI algorithms represents a big step forward in mitigating the environmental impact of AI systems. These algorithms prioritize sustainability by incorporating energy-efficient procedures and encouraging environmentally beneficial behaviour throughout the AI lifetime. Green AI algorithms provide real solutions for decreasing the carbon footprint of AI computations by combining resource optimization, renewable energy use, and carbon-aware techniques. Green AI algorithms optimize resource allocation to ensure that computational tasks are completed with minimal energy use. This not only lowers running expenses but also minimizes AI systems' environmental effects by cutting greenhouse gas emissions. Furthermore, promoting renewable energy sources for AI model training helps to reduce dependency on fossil fuels and shift to cleaner energy options.

Furthermore, carbon-aware optimization approaches play an important role in reducing the environmental impact of AI computing. Green AI algorithms help organizations achieve their goals while reducing environmental harm by taking into account the carbon footprint of various computational operations and choosing low-emission strategies. The incorporation of green AI algorithms into AI systems creates prospects for emission reduction and energy optimization in a variety of industries. By giving insights and recommendations for sustainable operations, these algorithms enable businesses to embrace environmentally friendly practices and contribute to a greener world.

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