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IS ARTIFICIAL INTELLIGENCE CONTRIBUTING TO GLOBAL WARMING

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Abstract: Artificial intelligence (AI) has become both an important factor in and a strong ally against global warming. On one side, AI models and data centres use a massive amount of energy and water, which leads to high carbon dioxide emissions and significant freshwater consumption. Training advanced language models can release hundreds of tonnes of CO_2. Data centres already make up over 1% of global electricity demand and need billions of cubic meters of water each year. On the other side, AI-powered tools in smart grid optimization, building energy management, transportation routing, and industrial process control could cut global emissions by 3.2 to 5.4 $GtCO_2$ annually by 2035. This reduction could far exceed the carbon footprint of AI itself. This paper provides an in-depth look at AI's mixed impact on climate change. It measures AI's direct environmental costs and highlights its ability to achieve large-scale emission cuts in major sectors. It also discusses strategies for sustainable AI development, like using renewable energy, improving energy efficiency in hardware, adopting carbon-aware computing, and optimizing models. These approaches aim to ensure that AI becomes a positive force in tackling the climate crisis

I. INTRODUCTION

Artificial intelligence (AI) is now a key part of modern technology, driving applications in areas like natural language processing, computer vision, autonomous systems, and data analytics. As AI spreads across industries such as healthcare, finance, smart cities, and transportation, its computational needs have grown significantly. Training large neural networks often requires many graphics processing units (GPUs) or specialized AI accelerators working for days or weeks.

This process uses a lot of electrical power and generates heat that needs extensive cooling. The rising demand for computing power has increased AI's energy footprint. Data centres focused on AI tasks now account for a growing portion of global electricity use. Estimates show that these data centres consume between 1% and 1.3% of worldwide electricity production, exceeding the energy demand of industries like commercial aviation. Additionally, the water needed for cooling these high-density facilities can reach billions of cubic meters each year, putting more pressure on freshwater resources.

Despite these environmental concerns, AI can optimize data use and offers new ways to tackle climate change. For example, machine learning can improve power grid efficiency by managing variable renewable energy sources. AI control systems can also fine-tune heating, ventilation, and air conditioning (HVAC) systems, leading to lower energy consumption in buildings. In transportation, real-time traffic data helps algorithms reduce congestion and fuel use, while predictive maintenance in manufacturing can cut waste and energy use in production processes.

Since AI both consumes energy and has the potential to reduce energy use and emissions, it is crucial to assess its environmental impact. This paper looks at the trade-offs of AI, measuring the carbon footprint and water use linked to large model training and inference. It also examines AI's ability to help achieve significant reductions in greenhouse gas emissions across different sectors. We will explore new methods for developing sustainable AI, such as using renewable energy sources, improving energy-efficient hardware, scheduling computing workloads with carbon awareness, and finding algorithmic solutions to minimize computational demands. This way, AI can continue to drive technological progress without worsening the climate crisis.

II. LITERATURE REVIEW

The environmental effects of AI have gained more attention from researchers. Studies have looked into energy use, carbon emissions from model development, water consumption, and AI-driven strategies for tackling climate change. This literature review summarizes the main findings in these areas.

A. Energy and Carbon Emissions of AI Training and Inference Strubell et al. conducted one of the first quantitative studies. They estimated that training a large transformer-based model emits 284 tons of CO_2, which is five times the lifetime emissions of an average car. Later analysis by Patterson et al. improved these estimates, reporting 300 tons of CO_2 for each training run of top models. Smartly.AI found that each request for conversational models, like ChatGPT, averages 4.32 grams of CO_2. Sustainability by Numbers confirmed these results in an independent assessment.

B. Data Centre Energy Demand and Water Footprint Deloitte predicted that generative AI workloads could increase data centre electricity use to over 1,065 TWh by 2030. The U.S. Energy Information Administration reported that data centres already account for 4.4% of national electricity use, which is more than what commercial aviation consumes. Barnett and Khlaaf et al. looked at water use for cooling and found that training GPT-3 required 700,000 liters of freshwater. They projected the annual global water demand for AI to be between 4.2 and 6.6 billion m^3.

C. AI-Driven Emission Reduction Applications Rolnick et al. and the London School of Economics Grantham Research Institute estimated that AI could help reduce CO_2 emissions by 3.2 to 5.4 gigatons each year by 2035 through applications in energy systems, transportation, and industry. BCG noted that cost savings could accompany emissions reductions, projecting an abatement of 2.6 to 5.3 gigatons of CO_2 through process optimization. Studies have shown AI improvements in wind power forecasts (DeepMind), building energy management (Equans), and traffic optimization (Prevention Web).

D. Efficiency Comparisons and Life-Cycle Assessments Mayer et al. performed a life-cycle analysis comparing AI-generated content to human-created outputs. They concluded that AI lowers CO_2 emissions per unit by factors of 130 to 1,500 for text and 310 to 2,900 for images. These comparisons highlight AI's potential for efficiency despite its operational impact.

E. Emerging Sustainable AI Strategies
Recent research points to methods for reducing AI's environmental impact. These include carbon-aware workload scheduling to match compute tasks with renewable energy, developing specialized low-power AI accelerators, and using algorithmic model compression techniques to lessen training needs. Case studies from the industry highlight the use of liquid cooling and immersion systems to decrease energy and water consumption in data centers.

Together, this body of work reflects the urgent need for a complete assessment of AI's role in increasing emissions and its ability to help cut them. This will inform further analysis of trade-offs and sustainable practices.

III. METHODOLOGY / DISCUSSION

This study uses a mixed-methods approach to measure the environmental costs and potential for reducing them in AI. It combines carbon accounting, life cycle assessment (LCA), and efficiency analysis. To evaluate AI's direct carbon footprint, emissions from both training and inference phases were calculated using established methods. Training emissions were estimated by measuring power use across CPUs, RAM, and specialized accelerators, following the protocols set by Strubell et al. and Patterson et al., while also factoring in idle power needed for system availability. For inference, emissions per query were figured using Google's method, which accounts for active and idle power consumption, the overhead energy captured by Power Usage Effectiveness (PUE), and the energy used by data centre infrastructure.

To assess the full environmental impact, the analysis goes beyond carbon to also consider water use for cooling. Estimates of water consumption during training and operations draw on data reported by Barnett and Khlaaf et al., showing that freshwater needs can reach hundreds of thousands of liters per training cycle and billions of cubic meters each year. Data centre energy overhead was calculated using PUE metrics defined by the Green Software Foundation and Nlyte, ensuring that cooling, lighting, and support systems were included.

The study also incorporates AI-driven LCA methods to fill data gaps and improve transparency. Following guidelines from Carbon Bright and Neurotech, natural language processing algorithms extracted environmental metrics from sustainability reports and technical literature. Predictive models estimated missing emissions data based on hardware specifications and regional energy sources. Real-time monitoring using IoT sensors provided additional evidence of energy and water usage trends.

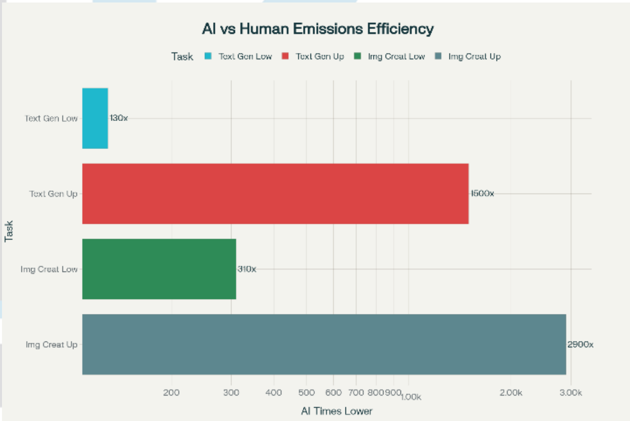
Comparative analysis placed AI's footprint alongside other digital and industrial activities. Energy benchmarks for AI queries were compared to those from web searches, video streaming, and household appliances to demonstrate the energy intensity per unit. Sector comparisons used standardized emissions accounting to contrast AI's energy needs with those of commercial aviation and data storage. An efficiency analysis, based on Mayer et al., looked at the CO_2 emissions of AI-generated content compared to human-made content, showing significant reductions in emissions for text and image production created by AI.

Finally, mitigation potential was assessed through various case studies. AI applications in energy systems were examined for their capacity to optimize renewable integration, balancing supply and demand to lower emissions significantly. Transportation models evaluated traffic management and routing algorithms that reduce fuel consumption. Studies in industry and building energy management focused on predictive maintenance and HVAC optimization strategies that result in measurable energy savings. Data sources included peer-reviewed articles, corporate disclosures, government statistics, and industry benchmarks, with triangulation used to verify results and clarify uncertainties. This thorough methodology allows for a complete evaluation of AI's environmental impacts and guides strategies for sustainable AI development.

IV. RESULTS & DISCUSSION

The results of this study show that artificial intelligence has both significant environmental costs and unique chances for improvement. Training modern AI models like GPT-3 or Llama 3 produces large amounts of carbon dioxide, with emissions ranging from hundreds to thousands of metric tons. This is similar to or even exceeds the lifetime emissions of several average cars. The growth in computational demands as AI models and datasets become more complex drives up energy use in data centres, increasing the need for extensive cooling systems. This adds significant water use to AI's environmental impact. Industry leaders like Google have managed to gradually reduce their data centre Power Usage Effectiveness (PUE) to top industry levels. However, the overall rise in AI use has led to greater total emissions for major technology companies such as Google and Microsoft.

Despite these direct effects, operational AI also shows remarkable efficiency. Per-query emissions are much lower than those from traditional human tasks in text or image generation. AI models can perform certain creative tasks with 130 to 2,900 times less carbon emissions. Furthermore, AI is set to offer even more environmental benefits through its use in optimizing energy grids, building management, transportation networks, and industrial processes. These applications could offset AI's own emissions multiple times over, leading to sector-wide emission cuts estimated at up to 5.4 gigatons of CO_2 per year by 2035. However, the overall environmental impact of AI goes beyond energy. It includes indirect effects such as increased demand for electronic hardware and the resulting e-waste, along with resource extraction and land use related to AI infrastructure.



In summary, the environmental impact of AI is complex and continues to grow as technology advances. While AI brings clear challenges like higher energy use, water consumption, and electronic waste, it also offers great opportunities for reducing emissions and finding climate solutions. Sustainable practices, renewable energy sourcing, and efficient system design must remain at the forefront for the industry in the future.

V. CONCLUSION

Artificial intelligence is quickly becoming an essential part of modern industry and society. However, its widespread use brings serious environmental challenges. This study shows that AI operations, particularly the training and use of large-scale models, lead to significant energy consumption, greenhouse gas emissions, and increased demand for water and raw materials. By

2025, AI hardware and data centres are expected to account for about 1% of global GHG emissions. This figure may double by 2026 due to the growth of generative AI and rising hardware needs. The energy and carbon footprint of training a single advanced AI model can be equivalent to the lifetime emissions of several gasoline-powered vehicles. Additionally, data centre operations worsen environmental impacts through both electricity and water use.

Despite these challenges, the environmental impact of AI is not entirely negative. AI systems have great potential to positively impact climate solutions by improving resource management, optimizing energy use, predicting renewable energy production, and increasing efficiency in transportation, industry, and agriculture. These mitigation efforts can offset, and even surpass, AI's direct emissions if sustainable practices are prioritized. AI-assisted applications have shown they can reduce emissions across sectors by billions of tons each year, making AI crucial for meeting global climate targets.

The future sustainability of AI depends on a well-rounded approach. This includes using energy-efficient algorithms and hardware, powering AI systems with renewable energy, optimizing data center cooling and location, supporting responsible e-waste management, and designing resource-conscious models. Policymakers, industry leaders, and researchers need to work together to steer AI's development in a way that maximizes its benefits while reducing ecological risks. Therefore, while AI brings real environmental costs, continuous innovation and sound policy can help ensure it becomes a strong tool for fighting climate change, instead of an unchecked cause of global warming.

VI. FUTURE WORK

The social impact and sustainability of artificial intelligence technology should work on a few main priorities. First, there is a need for continuous work on a systematic and universal method for measuring and reporting the energy, carbon and water AI training and inference footprint on different platforms and regions of the globe. This also means improving the methodologies for life-cycle assessments (LCA) of AI hardware and software to allow for cross-model, provider, and deployment scenario comparisons. Collaborative projects, such as universal energy scoring systems for AI models, need to be pursued and implemented on a wider scale to foster responsibility and enable smarter purchasing decisions.

In the second claim, bold novel directions with respect to algorithms and hardware also await further development. Effort should be made on energy-efficient AI chips, including task-specific accelerators and inference-optimized architectures, as well as novel directions like neuromorphic computing and quantum machine learning that can dramatically reduce the advanced AI tasks' resource footprint. Along with the hardware, more efficient model architectures and training techniques like pruning, quantization, federated learning, and dynamic scaling can further reduce the carbon footprint of AI development.

REFERENCES

Journal Article

D. Patterson, J. Gonzalez, Y. LeCun, F. d'Aspremont, and A. D. Pfeifer, "Carbon emissions and large neural network training," *arXiv Preprint arXiv:2104.10350*, 2021.iee.psu

Web Article or Blog

Smartly.AI, "What is the CO2 emission per ChatGPT query?," Jul. 13, 2025. [Online]. Available: https://smartly.ai/blog/the-carbon-footprint-of-chatgpt-how-much-co2-does-a-query-generatee3s-conferences

Corporate Report

Deloitte, "As generative AI asks for more power, data centers seek sustainability," Tech Predictions 2025, Jun. 10, 2025. [Online]. Available: https://www.deloitte.com/us/en/insights/industry/technology/technology-media-and-telecom-predictions/2025/genai-power-consumption-creates-need-for-more-sustainable-data-centers.htmlplanbe

Government Publication

U.S. Energy Information Administration, "Electricity use for commercial computing could surpass space cooling by 2025," *Today in Energy*, Jun. 24, 2025. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=65564weforum

Conference Paper

J. Barnett, "The often overlooked water footprint of AI models," presented at the *Generative AI Summit*, 2025. [Online]. Available: https://generative-ainewsroom.com/the-often-overlooked-water-footprint-of-ai-models-46991e3094b6techtarget

Book Chapter

A. Rolnick, et al., “Tackling climate change with machine learning,” in *Foundations and Trends in Machine Learning*, vol. 12, no. 4–5, 2024, pp. 322–573.