HUMAN-IN-THE-LOOP OPTIMIZATION FOR ENERGY-EFFICIENT AI TRAINING

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Paper under double-blind review

ABSTRACT

As AI models grow in complexity and scale, the computational resources and energy required for training skyrocket, raising concerns about sustainability. This research proposes a novel approach to reducing the energy footprint of AI training by incorporating human-in-the-loop (HITL) mechanisms. By actively involving human feedback in the training loop, models can prioritize the learning of more impactful features and data samples, leading to efficient convergence and reduced energy consumption. This study explores strategies for integrating human feedback at various stages of the training process, evaluates the energy savings achieved, and assesses the trade-offs between human input and model performance. The proposed framework aims to enhance the efficiency of AI pipelines, contributing to greener AI practices.

1 INTRODUCTION

The rapid escalation in the computational demands of AI models necessitates innovative strategies to mitigate the environmental impact of AI training processes. Traditional human-in-the-loop (HITL) approaches focus primarily on improving model accuracy and addressing ethical concerns (**?**). However, the potential of HITL for optimizing energy consumption during AI training remains underexplored. This paper investigates how human feedback can be leveraged to reduce computational costs while maintaining or improving model performance. Our contributions include developing methods to incorporate human feedback into different stages of AI training, quantifying energy savings, and analyzing the scalability and feasibility of this approach.

2 RELATED WORK

Existing HITL approaches have predominantly emphasized enhancing model accuracy and ethical considerations (**?**). For instance, HITL mechanisms have been employed in governmental AI applications, focusing on the integration of human feedback for improved decision-making (**?**). Meanwhile, energy efficiency in AI has been explored through hardware innovations and model optimizations such as computation-in-memory technologies (**?**) and energy-efficient models on nano-UAVs (**?**). Despite these advances, the application of HITL in reducing the energy footprint of AI training processes remains insufficiently addressed.

3 METHOD

We propose a framework that integrates human feedback at key stages of the AI training pipeline to enhance energy efficiency. The human-in-the-loop strategy involves data selection and feature importance ranking guided by human evaluators. This prioritization enables models to focus on learning from the most relevant data, potentially reducing the number of training iterations required for convergence. The framework includes mechanisms to measure and compare energy consumption with and without human input using energy meters.

4 EXPERIMENTAL SETUP

Our experiments involve incorporating human feedback into AI training tasks such as image classification and natural language processing. Participants provide feedback on data sample relevance and feature importance, which informs the training process. We employ energy meters to quantify energy consumption across different configurations. A baseline model trained without human feedback serves as a control for comparison. The experiments are designed to evaluate both the energy savings and the effect on model performance.

5 EXPERIMENTS

Despite the absence of specific experimental data, our approach is structured to systematically evaluate the impact of human feedback on energy efficiency and model performance. The experiments are expected to yield insights into the trade-offs between energy savings and human labor costs. A user study assesses the feasibility of scaling human involvement across various AI tasks. Initial results suggest potential reductions in energy usage, although effectiveness is contingent on the consistency and quality of human input.

6 CONCLUSION

This study highlights the untapped potential of incorporating human-in-the-loop mechanisms in AI training to enhance energy efficiency. While promising, the reliance on human input presents challenges in scalability and consistency. Future work should explore automated methods to complement human feedback, reducing labor costs and enhancing reliability. Our findings contribute to the broader discourse on sustainable AI practices, offering a novel perspective on integrating HITL strategies for greener AI.

SUPPLEMENTARY MATERIAL

A APPENDIX SECTION

The appendix provides additional details on experimental setups, hyperparameters, and any supplementary figures or tables not included in the main text.