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GREEN AI AND SUSTAINABILITY: A COMPARATIVE ANALYSIS OF MLP,CNN ,AND TRANSFORMERS ON ENERGY CONSUMPTION AND CLASSIFICATION ACCURACY

Dr. Nutan Krushnakant Sawant Department of Information Technology, SIES (Nerul) College of Arts, Science and Commerce(Autonomous)

ABSTRACT
The increasing computational demand of deep learning models has led to concerns about their energy consumption and environmental impact. This study compares three widely used neural network architectures—Multi-Layer Perception (MLP), Convolution Neural Network (CNN), and Vision Transformers (ViT)—on the MNIST dataset, analyzing both classification accuracy and energy efficiency. Using the Code Carbon library, we measure the energy consumption of each model during training and inference. The results demonstrate that Selecting the appropriate model architecture involves balancing accuracy, training time, energy consumption, and environmental impact. The MLP model offers a favorable trade-off for applications where computational resources and environmental considerations are critical. In contrast, the CNN and ViT models may increased computational and environmental costs.
Keywords: AI, sustainability, CNN, MLP,VIT

Introduction
Artificial Intelligence (AI) algorithms have become integral to modern society, driving advancements across various sectors, including healthcare, finance, and environmental management. Their ability to process and analyze vast amounts of data has led to significant improvements in efficiency and decision-making. However, the rapid proliferation of AI technologies has raised concerns regarding their environmental impact, particularly in terms of energy consumption and carbon emissions.

Training sophisticated AI models, such as large language models and deep neural networks, requires substantial computational resources. This intensive processing demands high- performance hardware, leading to increase energy consumption. For instance 2023 report from the Columbia Climate School estimated that training a single AI model can emit over 626,000 pounds of CO_2, equivalent to the emissions of five cars over their lifetimes.
(news.climate.columbia.edu)

The environmental footprint of AI is further exacerbated by the energy sources powering data centers. associated with AI operations are significantly higher. Conversely, data centers powered by renewable energy sources exhibit are reduced environmental impact.
In this study, Multi- Layer Perception (MLP), Convolution Neural Network (CNN), and Vision Transformer (ViT) models trained on the MNIST dataset. We examine how different architectures influence energy consumption, training time, and overall environmental impact.

Methodology
Dataset
The MNIST dataset is a widely used benchmark for image classification, containing 70,000 grayscale handwritten digit images (28×28 pixels), with 60,000 for training and 10,000 for testing. Due to its simplicity and effectiveness in evaluating machine learning models, it remains a standard dataset in

research. For this study, 12,000 random samples were selected from the original dataset to reduce execution time.

Models and Architectures

To examine the balance between performance and energy efficiency, we implemented the following models:

MLP (Multi-Layer Perceptron): A simple feedforward neural network with two fully connected layers. MLPs process flattened image inputs efficiently but lack spatial awareness.

CNN (Convolutional Neural Network): A model optimized for image processing that incorporates convolutional layers, max pooling, and fully connected layers. CNNs excel in image-related tasks due to their ability to capture spatial hierarchies.

ViT (Vision Transformer): A Transformer-based model that processes image patches using self-attention mechanisms, capturing non-local dependencies to enhance accuracy.

Each model was trained using PyTorch, and energy consumption was monitored during both training and inference phases. The Code Carbon energy tracking library was used to estimate CO_2 emissions based on the energy consumed.

RESULTS AND DISCUSSION:

Table1:Classification Accuracy

Model	Accuracy(%)
MLP	93.80
CNN	95.95
ViT	94.40

MLPs and CNNs are generally more computationally efficient compared to ViTs, especially on smaller datasets. ViTs have a higher number of parameters and require more computational resources, which can lead to longer training times.

While ViTs have demonstrated state-of-the-art performance on large-scale datasets, their performanceonsmallerdatasetslikeMNISTmaynotalwayssurpassthatofCNNs.Thissuggests that the inductive biases inherent in CNNs are beneficial for tasks with limited data.

Table2:Energy Consumption Analysis

Model	**Energy Consumption (kWh)**	**CO_2Emissions(kg)**
MLP	0.002	0.001
CNN	0.016	0.004
ViT	0.048	0.013

These findings emphasize the environmental impact of training deep learning models. The MLP's simpler architecture provides computational efficiency while consuming less energy and producing lower CO_2 emissions. In contrast, the CNN and ViT models, though capable of achieving higher accuracy, incur greater environmental costs due to their increased complexity.

This highlights the need to account for environmental considerations when designing and deploying AI models, particularly as the demand for more advanced architectures continues to rise

Table3:Training Time Comparison

Model	TrainingTime (seconds)
MLP	16.18seconds
CNN	128.24seconds
ViT	367.47seconds

These findings illustrate the trade-off between model complexity and training efficiency. While more advanced models like CNNs and ViTs can achieve higher accuracy, they require longer training times. In contrast, simpler models like MLPs train more quickly but struggle to capture spatial hierarchies in images as effectively as CNNs.
ViTs, in particular, demand significantly more training time due to the computational overhead of self-attention mechanisms, leading to increased power consumption and a greater environmental impact when training deep learning models.

KEY FINDINGS:

Accuracy vs. Computational Efficiency:

The CNN model achieved the highest accuracy (95.95%) but required the longest training time (128.24 seconds) and consumed more energy (0.016 kWh) than the MLP.
The ViT model, while maintaining a high accuracy of 94.40%, had the longest training time (367.47 seconds) and the highest energy consumption (0.048 kWh).
The MLP model demonstrated the shortest training time (16.18 seconds) and the lowest energy consumption (0.002 kWh), with an accuracy of 93.80%.

Environmental Impact:

The MLP model's minimal energy consumption and lower CO_2 emissions make it the most environmentally sustainable option compared to CNN and ViT models.
The ViT model's higher energy usage and CO_2 emissions indicate a greater environmental impact during training.

Trade-off Between Performance and Efficiency:

While CNN and ViT models deliver higher accuracy, they come at the cost of increased computational demands, extended training times, and higher environmental impact.
The MLP model offers a balance between performance and efficiency, achieving competitive accuracy with reduced computational and environmental costs.

CONCLUSION:

Selecting the right model architecture requires weighing accuracy, training time, energy consumption, and environmental impact. The MLP model provides a favorable trade-off for scenarios where computational resources and environmental concerns are paramount. On the other hand, CNN and ViT models may be preferred when the need for higher accuracy justifies the increased computational and environmental costs. Adopting Green AI practices is crucial to minimizing the environmental impact of deep learning. Organizations and researchers should prioritize efficiency-driven model design, rather than focusing solely on accuracy. Hybrid models that integrate CNNs with Transformer components could offer an effective balance between performance and sustainability.

FUTURE ENHANCEMENT:

The evolution of deep learning architectures towards greater efficiency and sustainability is essential for the responsible progress of AI technologies. Future advancements should aim to create models that strike a balance between performance and environmental impact, ensuring that AI contributes positively to both societal and ecological well-being.

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