Watt for What: Rethinking Deep Learning's Energy-Performance Relationship

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Introduction

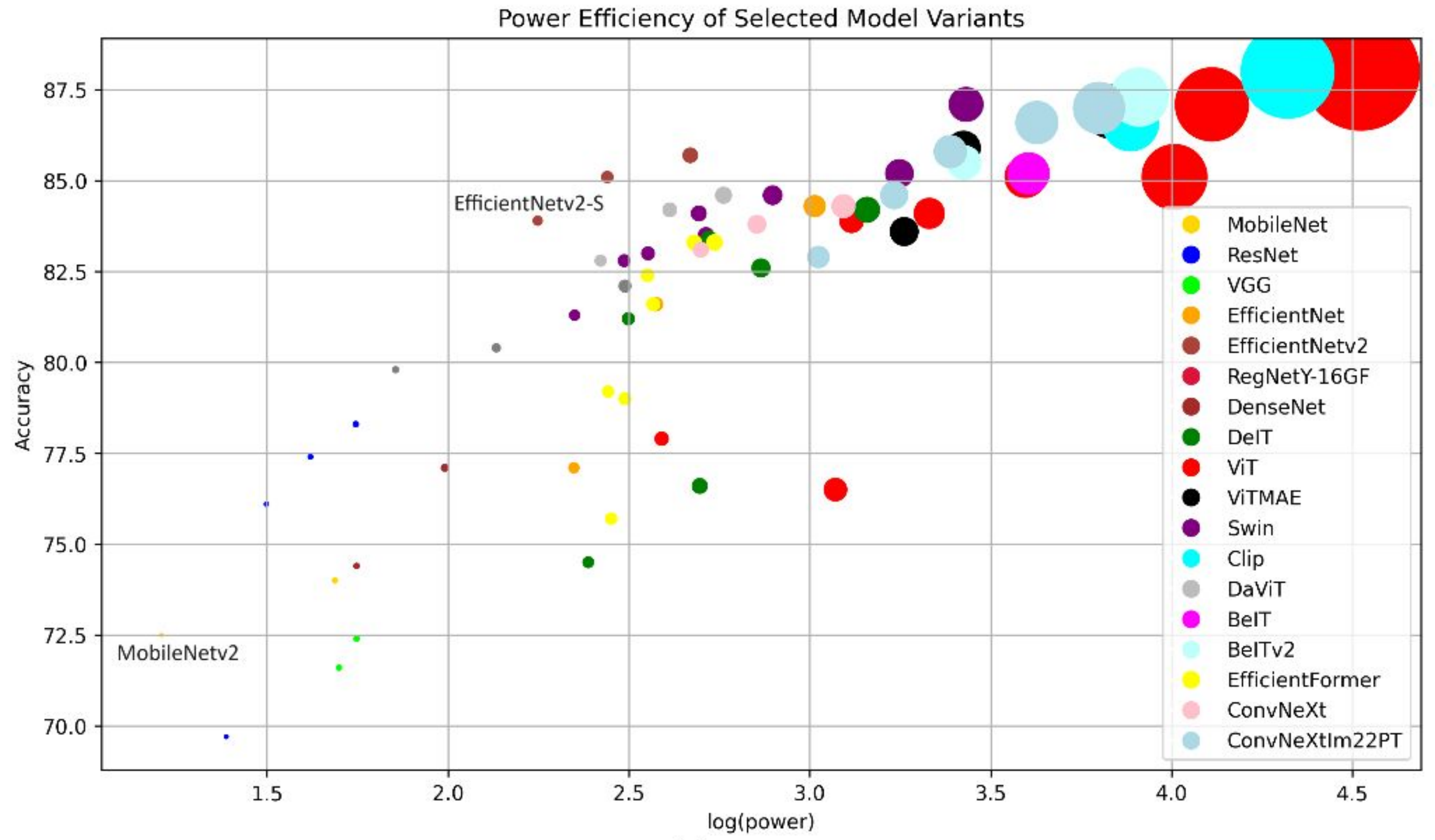
- **Energy Challenge:** Deep learning's increasing computational power demands are driving up electricity consumption, raising environmental and operational concerns.
- **Environmental Impact:** Training large AI models generates significant carbon emissions, which contributes to global climate change.
- **Resource Imbalance:** Smaller research entities are disadvantaged by limited access to computational resources, exacerbating inequity in the research landscape.
- **Proposed Solution:** This study introduces a metric that balances model accuracy with electricity consumption, promoting energy-efficient AI practices.
- **Goal:** To encourage sustainable deep learning and create a more equitable research environment while reducing environmental impact.

Proposed Metric

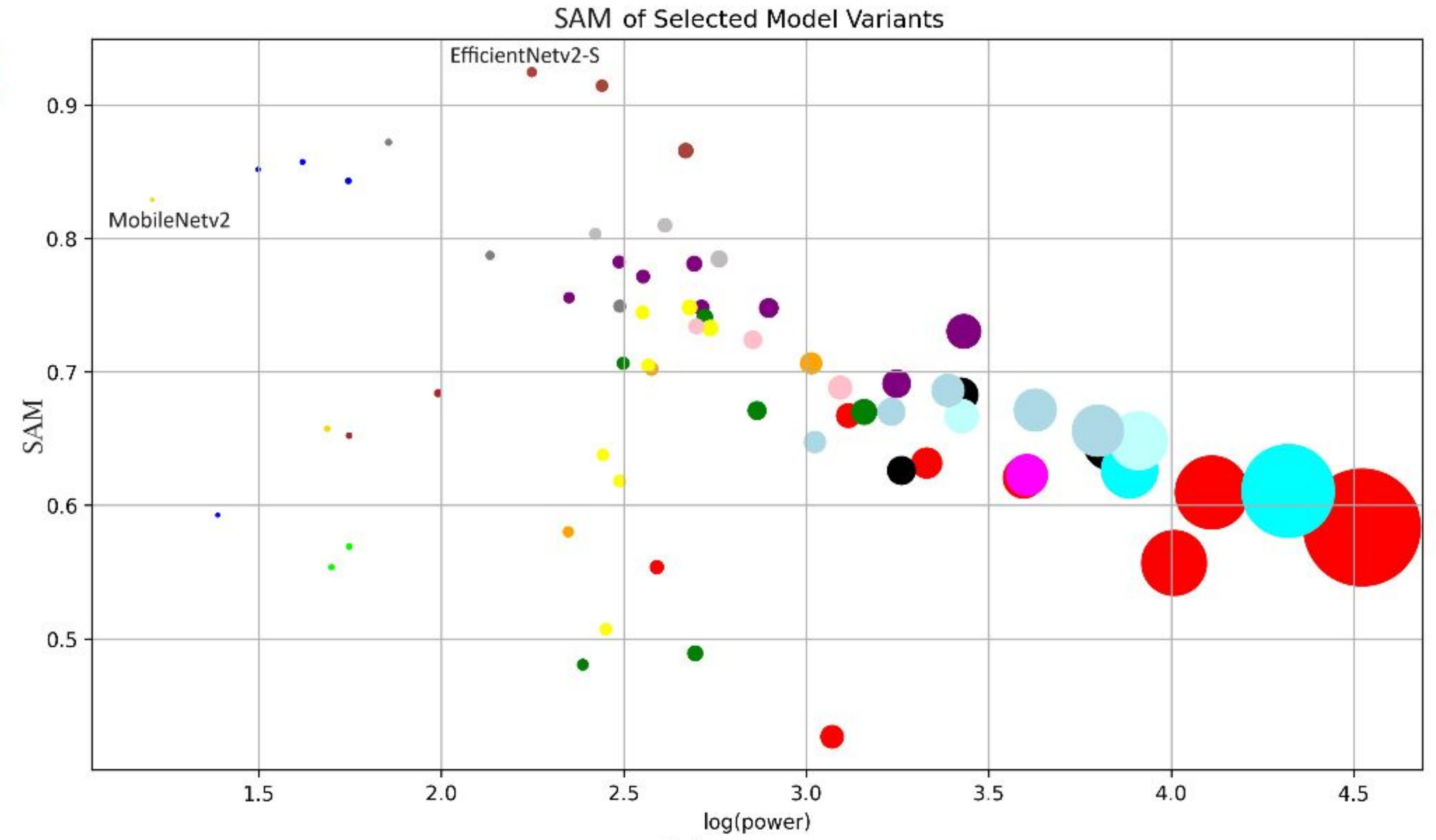
$$SAM = \beta \times \frac{accuracy^{\alpha}}{log_{10}(electricity)}$$

- **Energy Efficiency Focus:** The metric emphasizes the trade-off between model accuracy and electricity consumption, penalizing high energy use.
- **Logarithmic Scaling:** It uses a logarithmic scale to account for differences in power consumption across models, ensuring fair comparisons.
- **Accuracy-Power Balance:** The metric rewards models that achieve high accuracy with minimal energy usage, encouraging sustainable model development.
- **Equitable Comparison:** It allows smaller entities with fewer computational resources to compete fairly by prioritizing efficiency over raw computational power.
- **Scalability:** The metric can be applied across various deep learning tasks, from image classification to video action recognition, ensuring broad utility.

Results



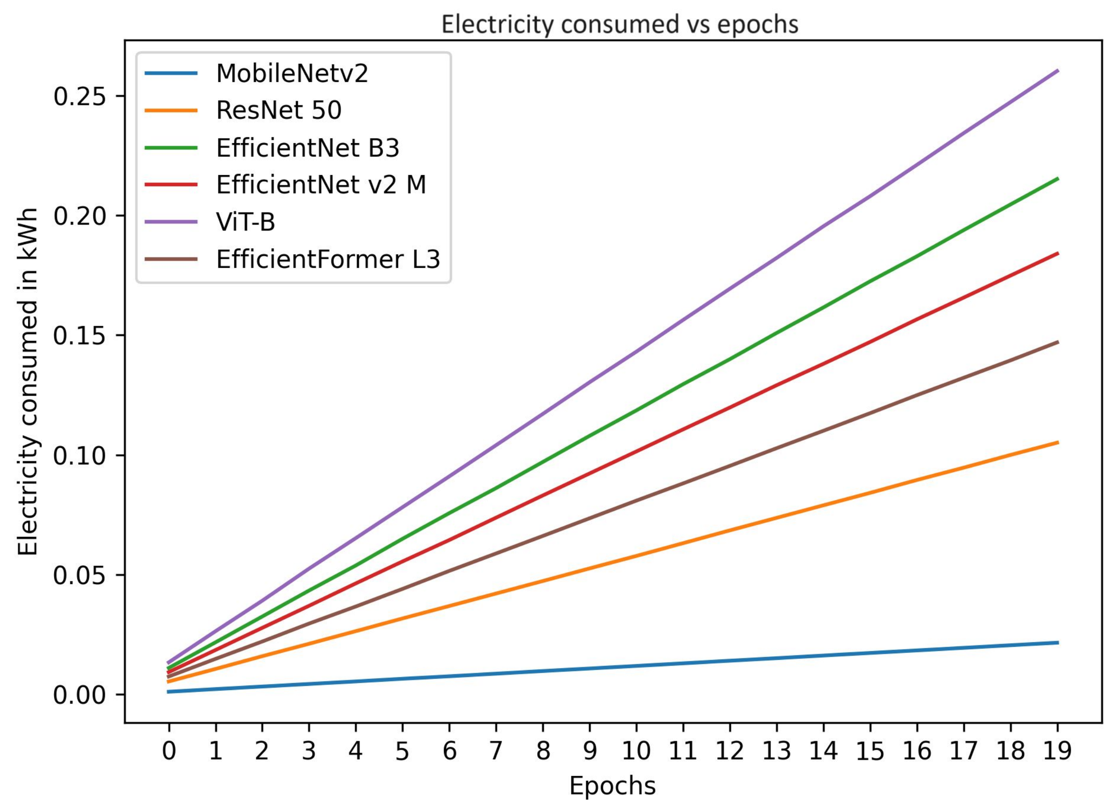
(a)

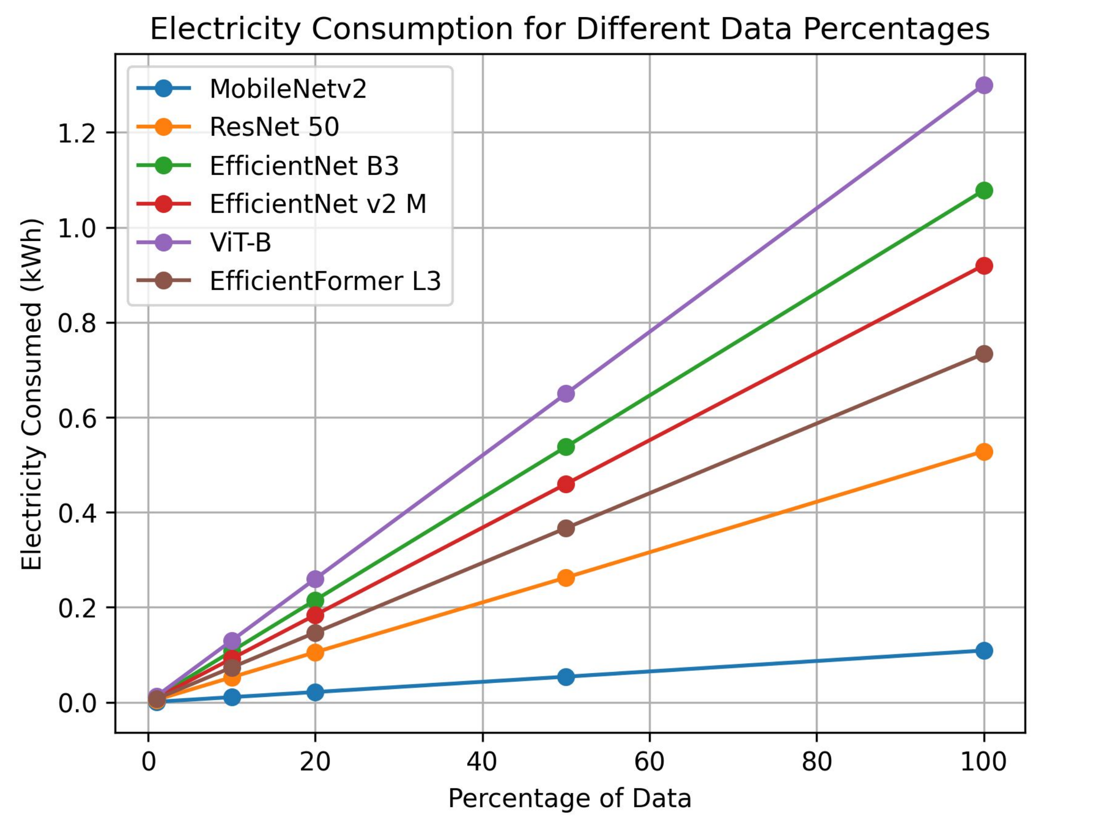


(b)

- Using SAM achieves a better balance between accuracy and electricity. In (a), lower accuracy models like MobileNet, ResNet, and EfficientNet are depicted poor compared to ViT-H. In (b), ViT-H and CLIP are penalized for high electricity usage, while EfficientNet and MobileNet rise.
  Marker points = electricity consumption.

How do we scale up?





- Given the time to reproduce results, a natural question is how can we scale things up in order to reach these results faster. (Left) Electricity Consumed Across Epochs: Linear Relationship Observed. (Right) Electricity Consumed Across Different Percentages of Data: Linear Relationship Observed.

Conclusion

- **Energy Efficiency Priority:** Balancing model accuracy with energy consumption is crucial to mitigate the environmental impact of deep learning.
- **New Metric:** The proposed metric offers a fair way to assess models by considering both accuracy and electricity use, encouraging more sustainable AI development.
- **Promoting Equity:** This approach levels the playing field, allowing smaller research entities to compete with well-resourced organizations based on efficiency.
- **Sustainable AI Future:** Encouraging energy-efficient practices in deep learning will reduce environmental harm while advancing innovation in a more equitable way.

Full paper: With results on Action Recognition and Instance Segmentation! Scan for more details:

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References

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