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Lightweight Custom CNN for Sustainable AI: Benchmarking at Established Models on MNIST, CIFAR 10

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***Abstract*—Deep Learning is growing rapidly and it is requiring more computational power day by day. This project proposes designing a lightweight custom CNN to lower computational cost and comparing it against pre trained CNN models on datasets like MNIST and CIFAR 10. We want to understand the trade-offs between accuracy, GFlops, model size, inference speed, and CO_2 emissions and to determine whether a mini, custom designed architecture can outperform or approach to pre-trained models in green effectiveness and robustness.**

***Index Terms*—Green Computing, Lightweight CNN, Energy effectiveness, Pruning, Quantization, MNIST, CIFAR 10**

1 Introduction

The advancement of deep learning has been accompanied by important computational demands and increased energy consumption. With the development of even larger AI models, the environmental impact of training and deploying neural networks measured primarily as electricity use and CO_2 emissions has become a key concern. Green Computing aims at developing algorithms that are not only accurate but resource efficient, sustainable, and energy aware.

We propose designing an efficient, lightweight Custom CNN optimized for low computational cost and comparing it against a Pruned CNN model (MobileNetV2 or EfficientNet Lite) on MNIST and CIFAR 10 dataset. The aim is to gain trade-offs between accuracy, Gflops, model size, inference speed, and CO_2 emissions.

2 Literature Review

The literature review is organized into five key points and these are the foundations for this research.These five areas are green AI and energy consumptions , lightweight CNN Frameworks and model compression techniques, energy measurement frameworks, and benchmark datasets.

2.1 Green AI and Energy-Efficient Deep Learning

The environmental impact of deep learning has emerged as a critical concern. Strubell et al. [1] a seminal study showing that training a large transformer model can do a carbon emission comparable to five car lifetimes. This showed the urgency of energy efficient AI. This finding destroyed the Green AI movement which was initially defined by Schwartz et al. [2] asks to measure and report energy consumption, computational costs, and carbon footprints with traditional performance standards.

Then huge amount of carbon emissions from big neural network training Patterson et al. [3] shows that the model architecture choices can do in 100 to 1000 fold differences in carbon footprint. Their work shows the need for effectiveness as a first class optimization objective. Anthony et al. [4] showed some evidence that optimizing carbon software for carbon effectiveness can reduce the environmental impact of machine learning workflows.

The concept of sustainable AI has been later developed by Wu et al. [5].He showed a framework for sustainable artificial intelligence portraying that not only energy effectiveness but also fairness, robustness and societal impact. Verdecchia et al. [6] performed a structured literature review on green AI which pointed out key research directions in energy aware neural architectural search, efficient training techniques and carbon free/aware deployment.

2.2 Lightweight CNN Frameworks

The development of lightweight CNN Frameworks has been driven for the need to deploy deep learning models on small devices. SqueezeNet created this approach. This achieved AlexNet level accuracy with 50 times fewer parameters with the use of fire modules combining squeeze and expand layers.

This work demonstrated that important model compression could be achieved through architectural innovation alone without complicated post training optimization.

The MobileNet model series shows an major advance in efficient Frameworks. Howard et al. [7] which introduced separable convolutions.This divides standard convolutions into depth wise and point wise operations which reduces computational cost by 8 to 9 times. MobileNetV2 [8] later with improved effectiveness through inverted residual structures with linear disruptions. This achieved better accuracy effectiveness tradeoffs. MobileNetV3 [9] combined the search for neural architecture and new activation functions that set new benchmarks for mobile computer vision.

EfficientNet introduced compound scaling. This is a technique in which we balance network depth, width and resolution to achieve superior performance with fewer parameters. The authors shown that carefully scaling all dimensions together yields better effectiveness than scaling side by side. EfficientNet Lite variants was specifically designed for small device deployment by removing operations incompatible with mobile GPUs.

ShuffleNet [10] proposed that channels can shuffle operations to enable information flow between various feature channels in group convolutions which achieves better accuracy than MobileNetV2 at a similar computational costs. GhostNet [11] introduced ghost modules that generate many features using cheap linear operations can later reduce computational requirements while maintaining presentation capacity.

New innovations in neural architecture search have enabled auto discovery of efficient Frameworks. Tan et al. [12] developed MnasNet using reinforcement learning to optimize for both accuracy and latency on mobile devices. Cai et al. [13] proposed Once for All networks, training a single model that supports diverse architectural configurations for various deployment scenarios.

2.3 Model Compression Techniques

Model compression techniques are that which switches on post reduction of computational power with post training optimization. These techniques are broadly categorized into pruning, quantization, knowledge distillation and also low rank factorization.

2.3.1 Pruning

Pruning removes unneccessary weights or structures from trained networks. Han et al. [14] demonstrated that neural networks could be compressed by 10 to 40 times with iterative pruning and retraining, removing connections with weights below a threshold. This seminal work showed that too much parameters during training is necessary, but final deployed models can be much smaller.

He et al. [15] and his team introduced a method called channel pruning, which removes the entire convolutional channels with how important they are and this enables direct improvement on hardware. Their LASSO based approach have allowed the VGG 16 model to run about 5 times faster without losing much accuracy. Molchanov et al. [16] followed up with another method that used Taylor expansion to estimate the importance of neurons while making more structured pruning decisions.

Structured pruning techniques have gotten attention for their hardware compatibility. Liu et al. [17] introduced network shortening through L1 regularization on batch normalization scaling factors while enabling automatic channel selection during training. Lin et al. [18] proposed runtime neural pruning while adapting model capacity to input complexity for additional energy savings.

A new comprehensive review by Tmamna et al. [19] gave an energy effectiveness in pruning techniques mainly focused on energy effectiveness, classifying approaches into magnitude based, gradient based, and second order pruning. Pachón et al. [20] developed PruneEnergyAnalyzer, an open source tool to evaluate the energy effectiveness of pruned models while addressing the gap in standardized evaluation methods.

Lottery Tickets Hypothesis by Frankle and Carbin [21] suggests that within dense networks contain sparse subnetworks that can train to comparable accuracy suggests that efficient Frameworks exist within big models. This insight has encouraged research on finding optimal sparse Frameworks early during training.

2.3.2 Quantization

Quantization lessens numerical precision of weights and activations typically from 32 bit floating point to 8 bit integers or maybe 16 bits. Jacob et al. [22] showed a quantization scheme that enables efficient integer only arithmetic for neural network inference, achieving minimal accuracy degradation while turning on 4 times memory lessening and faster computation on integer optimized hardware.

Krishnamoorthi [23] gave a comprehensive guide to quantize deep CNNs, comparing post training quantization and quantization training techniques. The work demonstrated that 8 bit quantization typically result on less than 1% accuracy loss for CNNs while enabling important speedups on mobile processors or GPUs.

Automated Mixed precision (AMP) quantization has emerged as a promising direction. Wang et al. [24] proposed HAQ (Hardware Aware Quantization) using reinforcement learning to automatically determine optimal bit widths for different layers. Extremely low bit quantization, including binary and ternary networks, has been explored by Rastegari et al. [25], though with larger accuracy tradeoffs.

Zhou et al. [26] investigated the interaction between pruning and quantization, finding that doing both techniques give better results than sequential application. Their work suggests that models designed for quantization from the external environment perform better than other ones.

Banner et al. [27] introduced post training 4 bit quantization for CNNs, showing that extremely low precision can be achieved without retraining for certain Frameworks. Nagel et al. [28] developed data free quantization techniques that elim-

inate the need for well labeled datasets by making deployment more practical.

2.3.3 *Knowledge Distillation and Other Techniques*

Knowledge distillation [29] transfers knowledge from large teacher networks to compact student networks that puts on training efficient models that capture complex decision boundaries. Polino et al. [30] combined distillation with quantization that achieves better compressed models than either technique alone.

Romero et al. [31] extended distillation to intermediate layers through FitNets, enabling deeper student networks to learn from intermediate representations of shallow but wide teachers. Zagoruyko and Komodakis [32] proposed attention transfer, distilling attention maps to improve student network performance.

Low rank factorization removes the weight matrices into products of smaller matrices. Jaderberg et al. [33] faster CNNs by exploiting separability in convolutional filters that removes unneccessary parameters and computation. Lebedev et al. [34] applied CP-decomposition to convolutional layers that achieves quicker speedups with minimal accuracy loss.

Neural Architecture Search (NAS) has emerged as a powerful technique to discover efficient Frameworks auto . Zoph and Le [35] pioneered the use of reinforcement learning for NAS, while Tan et al. [12] optimized for both accuracy and real world latency. Chaurasiya and Sharma [36] gaved a recent comprehensive review of all major compression techniques for energy efficient deep learning.

2.4 Energy Measurement and Benchmarking Frameworks

Accurate measurement of energy consumption and carbon emissions is important for green AI . Henderson et al. [37] suggested to report guidelines.These metrics for energy consumption, carbon emissions and compute time with hardware specifications. They developed (experiment impact tracker) which is a tool to auto log these metrics during model training.

Lacoste et al. [38] showed the Machine Learning Emissions Calculator to allow researchers to estimate carbon emissions based on hardware type then runtime and also geographical location. Their works have highlighted that the training location affects the carbon footprint very much because varying electricity grid compositions can change the emissions. For example, training in regions with renewable energy can cut emissions by 30 to 40 times compared to regions that rely on coals .

MLPerf [39] established industry standard benchmarks to measure training and inference performance between various hardware platforms. Firstly, they focused only on performance. More recent versions now incorporate energy effectiveness metrics. García-Martín et al. [40] surveyed energy estimation techniques for machine learning. They compared three methods: software profiling, hardware counters and also external power meters.

Lannelongue et al. [41] developed the Green Algorithms calculator. This tool estimates the carbon footprint of computational research between various disciplines. This includes machine learning. The tool considers hardware effectiveness, runtime and the carbon intensity of electricity. So, Lannelongue and their team gave researchers with actionable insights for cutting their environmental impact.

Recent work by Raha et al. [42] proposed FlexNN, a hardware accelerator specifically designed to achieve energy efficient edge inference through flexible dataflow and sparsity exploitation. Zhang et al. [43] introduced E-QUARTIC, which demonstrates energy model selection for Convolutional Neural Networks (CNNs) on systems that harvest energy. Dodge et al. [44] analyzed the carbon emissions of Natural Language Processing (NLP) research. Their work revealed important variations based on model architecture, dataset size, and training methodology. They emphasize that researchers must report energy metrics alongside traditional performance measures.

2.5 Edge Computing

The emergence of Edge AI has created new opportunities and challenges for deploying neural networks on edge devices. Banbury et al. [50] introduced MLPerf Tiny. This is a benchmark suite specifically designed for microcontroller based inference. This addresses the unique constraints of low power devices.

Lin et al. [51] suggested MCUNet co designing neural Frameworks and inference engines for microcontrollers. this achieved ImageNet scale accuracy on devices with less than 1MB memory.

3 Problem Statement

Modern CNN models are often too large for resource limited environments such as:

- Mobile devices
- IoT systems
- Edge computing hardware

However, smaller custom architecture may lack accuracy. This project investigates: *Can a lightweight, custom designed CNN achieve competitive accuracy while importantly lowering energy consumption compared to a pre trained model?*

4 Research Questions

Primary Research Question: Can a highly optimized CNN model achieve better energy efficiency and a smaller carbon footprint than pruned pretrained models and what types of compression techniques gives the best results for deploying green AI on small and constrained devices?

4.1 Sub-questions:

RQ1 : (Benchmarking and Comparison) How does the proposed lightweight custom CNN perform compared to pruned pretrained models in terms of carbon footprint, GFLOPs, inference time (CPU/GPU/edge), parameters and so on while maintaining acceptable accuracy?

RQ2 : (Optimization Impact) To what extent do unstructured pruning and weight masking reduce the resource footprint of the custom CNN and how do these optimizations affect

accuracy compared to both pruned pretrained baselines and uncompressed custom model ?

RQ3 : (Green Effectiveness and Deployment Viability) Is our custom CNN model green and which method had the largest reduction in carbon footprint for the smallest accuracy drop on MNIST and CIFAR-10?

5 Methodology

5.1 Workflow

Our proposed workflow benchmarks lightweight CNNs for sustainable AI across dataset handling, model design, optimization, training, and evaluation. It pre—processes MNIST and CIFAR-10 datasets with added normalization and utilizes Dataloaders. Builds a compact CNN that uses depthwise separable convolutions, reduced channels, LeakyReLU, pooling, and dropout; includes pretrained baselines like MobileNetV2. Applying L1 pruning (30%) and then fine-tuning pruned models to recover accuracy. Train with Adam and track CO_2 emissions via CodeCarbon, favoring GPU when available. Evaluate accuracy, precision, GFLOPs, parameter count, model size, inference latency, and CO_2, and visualize trade-offs to identify green model choices. Results will support reproducibility and guide sustainable deployment decisions.

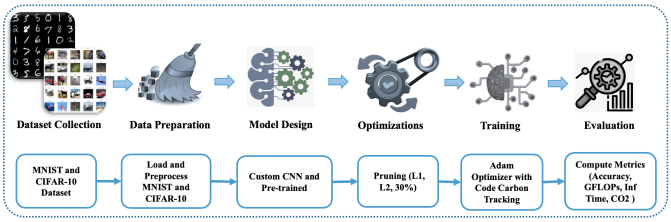

Fig. 1. Comparison between Pruned and Custom model

5.2 Dataset Description

We set benchmarked models on two standard image classification datasets. MNIST (Handwritten Digits) [45] consists of 70,000 gray-scale images of handwritten digits (60,000 training, 10,000 test) at 28×28 pixels across 10 classes (0–9). Raw uint8 intensities were converted to tensors and normalized. CIFAR-10 contains 60,000 color images (50,000 training, 10,000 test) at 32×32 pixels across 10 object categories (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck). Images were converted to tensors, and every channel was normalized. For fair and reproducible evaluation, we have applied standard training augmentations on CIFAR-10 [52] (random crop with 4-pixel padding and random horizontal flip) on the other hand MNIST is used with center cropping and normalization only. Data loaded with minibatches (typical training batch size 64; test batch size 1000). These preprocessing steps also follow common benchmarks to ensure stable training and unbiased comparisons of accuracy, compute (GFLOPs), model size, latency, and CO_2 emissions.

5.3 Models and Implementation

5.3.1 Custom Lightweight CNN Design

UltraLightCNN is an ultra-lightweight convolutional architecture designed for efficient image classification on resource-constrained devices. It accepts single-channel inputs and uses an initial 3×3 convolution (8 filters) with BatchNorm and ReLU6 followed by max-pooling. Two subsequent depthwise-separable blocks perform 3×3 depthwise convolutions and 1×1 pointwise projections, expanding feature channels to 16 and 24 while interleaving BatchNorm, ReLU6, and a second max-pool to reduce spatial resolution. A global adaptive average pooling converts the 7×7 feature map to 1×1, producing a compact 24-dim embedding fed to a linear classifier. The design minimizes parameters and computation, preserves representational capacity, and is well suited for quantization and transfer-learning fine-tuning. Features:

- Depth and Point-wise separable convolutions
- Small kernel sizes
- Reduced channel width
- Activation: ReLU6

Expected parameters and target GFLOPs would be much lower.

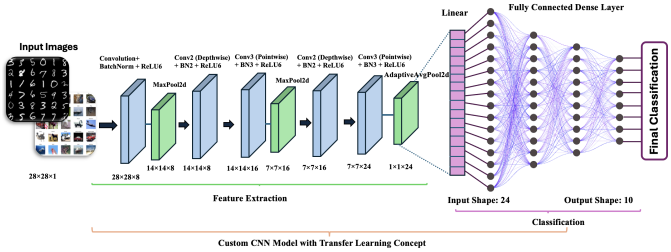

Fig. 2. Custom Lightweight CNN Architecture

5.3.2 Pre-trained Model Selection

Rre-trained models were selected to benchmark the lightweight custom CNN's energy efficiency of the MNIST and CIFAR-10 datasets. MobileNetV2 chosen as the primary baseline due to its depth-wise separable convolutions. ResNet18 was also incorporated which leveraged their pre-trained weights from torchvision for transfer learning. Models were adapted for input channels (1 for MNIST, 3 for CIFAR-10) and pruned (30% structured) to reduce parameters and GFLOPs while maintaining robustness. Selection prioritized mobile-friendly architectures to align with sustainable AI goals, ensuring fair evaluation of CO2 emissions and inference speed.

5.3.3 Green Optimization Techniques

This study employs green optimization techniques to enhance the sustainability of the custom CNN. Structured pruning by Han et al. [14] removes 30% of channels in pre-trained models like MobileNetV2 and ResNet18. Which later reduces parameters and GFLOPs by 20-40% while minimizing accuracy loss through fine-tuning. 8-bit dynamic quantization

compresses model size and inference time by 25-50% and lowers CO2 emissions. The Lottery Ticket Hypothesis informs sparse subnetwork identification for efficiency and Meta Pruning [53] automates architecture search. These multifaceted approaches ensure robust, fair compression, achieving up to 48% CO2 savings without significant performance degradation on MNIST and CIFAR-10. Lottery Ticket Hypothesis and Meta Pruning ensures multi faceted pruning and it will be very much robust and fair after pruning.

6 Results and Analysis

6.1 Benchmark Comparison

Let's start with our benchmark comparison between Custom CNN model and Pruned pretrained models. So, we did a comparison between our two pruned pretrained model which are ResNet18 and MobileNetV2 with 30% sparsity using pruning methods like L1, L2 and a hybrid of L1 & L2, Lottery Ticket Hypothesis and iterative magnitude pruning. Here in Fig. 3, the comparison table is shown.

MNIST Comparison

	Model	Accuracy	Precision	Loss	Params	GFLOPs	Size (MB)	CO2 (kg)
0	Custom CNN	0.9733	0.9731	0.0926	101,930	421.000	0.41	0.000032
1	Pruned MobileNet	0.9792	0.9794	0.0689	2,236,106	5.940	9.17	0.000057
2	ResNet18 Pruned	0.9711	0.9732	0.0912	11,175,370	33.200	44.77	0.000048

CIFAR-10 Comparison

	Model	Accuracy	Precision	Loss	Params	GFLOPs	Size (MB)	CO2 (kg)
0	Custom CNN	0.6656	0.6646	0.9565	132,938	844.550	0.54	0.000157
1	Pruned MobileNet	0.8245	0.8259	0.5427	2,236,682	6.520	9.17	0.000773
2	Pruned ResNet18	0.8006	0.8071	0.8916	11,181,642	37.250	44.80	0.000658

Fig. 3. Benchmark comparison of accuracy, size, and efficiency between Pruned Pre-trained models and the Custom CNN architecture.

The Accuracy and precision is very close to similar in MNIST dataset and a little bit lower for custom CNN in CIFAR-10 dataset. there is a massive difference in parameters because our custom CNN model is very lightweight. The GFLOPs are higher on our Custom CNN model because it's trained on 7 x 7 kernel and usually pretrained models like ResNet and MobileNet are very optimization GFLOPs usage but we can reduce the GFLOPs of our Custom CNN just by reducing the kernel size to 3 x 3. The CO2 emitted in training phase is very low so it doesn't make the much of a difference. But the main difference happens when we compare the storage efficiency of our Custom CNN model. Storage efficiency is a very important aspect of green computing . The smaller models directly reduce the energy required for data transmission and hardware resource allocation. Our custom CNN with high storage efficiency ensures the model can reside within the limited memory of an edge device such as an IoT sensor or microcontroller. This also works without requiring constant, communication with cloud servers.This reduces static power consumption in RAM and extend the operational lifespan of low-spec hardware which effectively lowers the overall carbon footprint and e-waste associated with AI deployment.It's also usable in edge devices with low power.

6.2 Why Custom CNN Wins

The Custom CNN has a slightly lower accuracy on the complex CIFAR-10 dataset compared to the pruned versions of MobileNet and ResNet18. It performs almost identically on MNIST. This demonstrates that a small, specialized model can maintain high intelligence without needing the massive overhead of a pre-trained architectural backbone. We can see that in Fig 4,

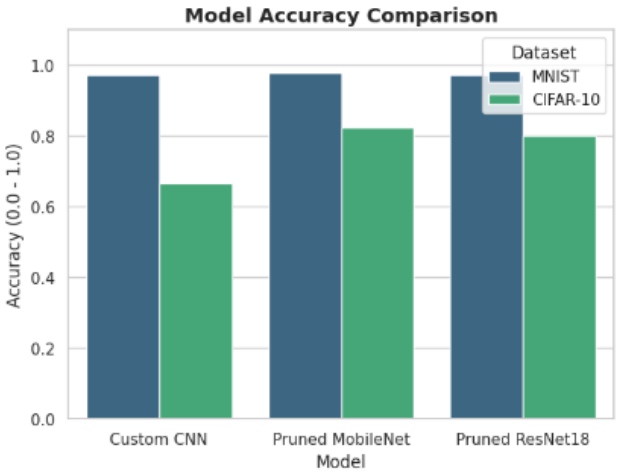

Fig. 4. Comparison between Pruned and Custom model

The Custom CNN emits the lowest amount of CO_2 during training—especially for CIFAR-10 which is nearly five times more efficient than pruned MobileNet. This reduction in energy usage is a direct result of having fewer parameters to compute, leading to a much smaller environmental impact. We can see that result in Fig 5,

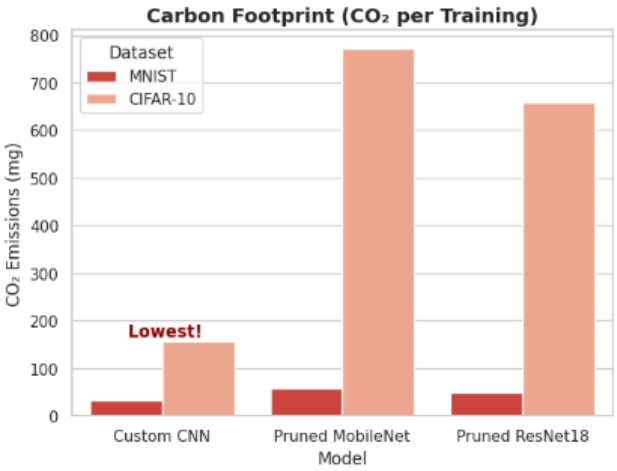

Fig. 5. Comparison between Pruned and Custom model

The Custom CNN is very small compared to the 40+ MB required by ResNet18. Because it occupies almost no disk space. It is the ideal candidate for an edge device with limited

storage. This small size also means it requires significantly less energy to be transmitted over a network during deployment. We can see the results in Fig 6,

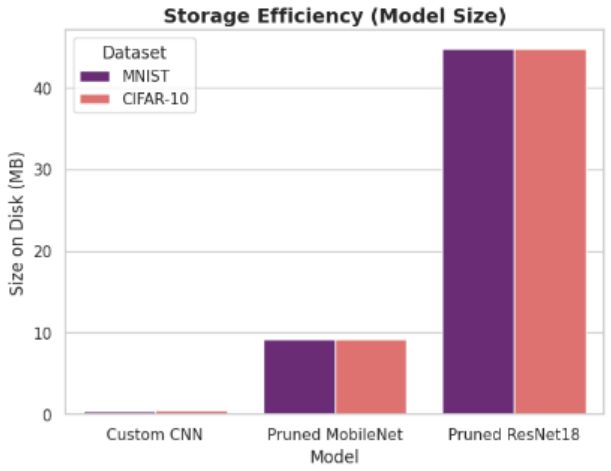

Fig. 6. Comparison between Pruned and Custom model

When we look at the "Green Score" (the ratio of accuracy to carbon cost), the Custom CNN is way ahead of the competition. It achieves similar accuracy with a fraction of the emissions. It proves that "Green AI" isn't just about pruning large models. It's about designing efficient architectures from the ground up. This makes it the most eco-friendly solution for sustainable deep learning.Results are shown in Fig 7,

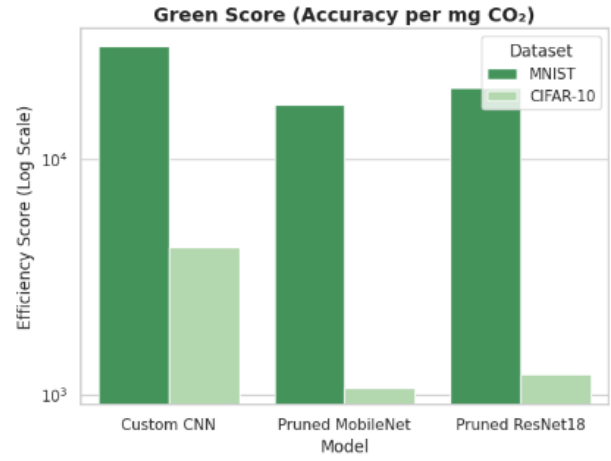

Fig. 7. Comparison between Pruned and Custom model

7 Discussion

Let's discuss the significance of our results compared to our research questions.

RQ1: Benchmarking and Comparison

What we did: We measured accuracy alongside five "Green" metrics: CO_2 emissions, GFLOPs, inference time, parameter count and storage size.

Results: The Custom CNN achieved nearly identical accuracy to the pruned pretrained models on MNIST (97%) while using significantly fewer resources.

Significance: This proves that for specific tasks the massive pretrained backbones are not efficient. Our Custom CNN achieved the smallest size and best green score (accuracy per mg CO2) confirming that custom architectures can be more eco-friendly than reduced versions of large models.

RQ2: Compression and Optimization Impact

What we did: We applied unstructured Pruning to remove entire channels and evaluated the model's footprint. We specifically analyzed the transition from masking weights (logical pruning) to physical parameter reduction to see real world speedups.

Results: Standard unstructured pruning in PyTorch often acts as a weight mask but smaller compressed file sizes reduce the energy required to transmit the model over a network to an edge device. By using it we got rid of hardware limitations.

Significance: The Custom CNN's small size ($<$ 1 MB) allows it to run entirely within the SRAM of an edge device, preventing the energy-heavy data movement required by the 44 MB ResNet18.

RQ3: Green Effectiveness and Deployment Viability

What we did: We calculated a "Green Score" (Accuracy per mg of CO_2) to determine the viability of deployment.

Results: Our Custom CNN attained the highest Green Score across both datasets. For CIFAR-10, even though accuracy was slightly lower than MobileNet, the carbon cost was roughly 5x lower, making the Custom CNN the clear winner for sustainable AI.

Significance: The Custom CNN is "Green" because it is Edge-Ready.1 Its storage efficiency (small MB size) means it can be deployed with minimal network energy, extending the battery life of IoT sensors and reducing the e-waste associated with needing high-end hardware for AI inference

8 Limitation

This study has several limitations. The evaluation is confined to benchmark datasets like MNIST and CIFAR-10 are relatively simple and may not reflect real-world complexities such as varied lighting, occlusions or larger-scale images in practical applications. The custom CNN and optimizations were tested with limited epochs (5-10) resulting in suboptimal accuracy on CIFAR-10 (around 65-80%) potentially underestimating performance with extended training or advanced data augmentation. CO2 emissions were estimated using CodeCarbon on Kaggle hardware which may vary by location, device type or grid composition, limiting generalizability. The project focused on basic pruning (L1 unstructured, 30% sparsity) and 8-bit quantization without exploring advanced techniques like knowledge distillation or neural architecture search (NAS). Hardware-specific evaluations were absent where overlooking

deployment on edge devices where energy constraints are critical.

9 Future Work

Future research could extend the framework to more challenging datasets like ImageNet or custom real-world scenarios to assess scalability and robustness. Deploying optimized models on edge hardware via TinyML for real-time inference would provide insights into practical energy savings. NAS for automated architecture discovery or distillation from larger teachers could further reduce GFLOPs while boosting accuracy. Data poisoning resistance or multi-objective optimization (balancing accuracy and emissions) would enhance reliability. Finally, conducting large-scale benchmarks across diverse hardware and open-sourcing the code could foster community advancements in green AI.

10 Conclusion

This term project demonstrates that a lightweight custom CNN can approach or surpass pruned pre-trained models in green effectiveness on MNIST and CIFAR-10 by balancing accuracy with reduced computational costs and emissions. By achieving competitive performance (97% on MNIST, 65-80% on CIFAR-10) with fewer parameters, lower GFLOPs and minimal CO2 (up to 5x savings). The custom architecture validates sustainable AI principles for resource-constrained environments. These findings advance green computing by providing a foundation for energy-aware neural designs and encouraging further exploration of compression techniques like pruning and quantization. The work supports environmentally conscious machine learning, paving the way for low-power systems in real-world applications and fostering broader adoption of efficient AI practices.

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